Consumer Acceptance of Novel Foods 2

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CHAPTER

18

Consumer acceptance of novel foods

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"The story so far: In the beginning, the Universe was created. This has made a lot of people very angry and been widely regarded as a bad move." ***Douglas Adams, The Restaurant at the End of the Universe***

18.1 Introduction

Many innovations face criticism when first launched. The ultimate success or failure of designs depends largely on favorable overall consumer response to those innovations (see, e.g., Gupta et al., 2012; Ronteltap et al., 2007; Siegrist, 2000). Novel foods fail due to the lack of consumer acceptance or even active consumer rejection of these products. Infamous examples of innovations that have suffered setbacks following negative consumer response are the introduction of genetically modified organisms in Europe (e.g., Frewer et al., 2013a) and food irradiation (Bruhn, 1995; Diehl, 2002). Consumer responses to novel foods depend on how consumers perceive the benefits, risks, and costs of the novel foods and their underlying technologies (Bearth and Siegrist, 2016; Ronteltap et al., 2007). Consumer perceptions and how they are combined into an overall evaluation of the novel food may systematically differ from expert assessments of the same product (Lazo et al., 2000; Siegrist and Gutscher, 2006; Slovic et al., 1995). In addition, consumers may perceive and decide on the benefits of a product in different ways depending on the specific use of the new technology (van Giesen et al., 2016), their situation, or the context of the food choice (Bagozzi et al., 2000).

To avoid unnecessary rejection of innovations, or to avoid investing in innovations that are inherently unacceptable to the public, it is vital to include consumer insights into the innovation process early on (Van Kleef et al., 2005). More specifically, we need insight into (a) which are the relevant perceptions of consumers in the context of food innovations and how they combine toward a final response and (b) the products in which this innovation is applied (Gupta et al., 2012; Ronteltap et al., 2011). This also implies that we need to know how to measure consumer perceptions reliably (Churchill, 1979; Reinders et al., 2013). Both these requirements are complicated by the fact that perceptions and decisions are in the mind of the consumer and cannot be measured directly.

One of the substantial efforts of (food-related) consumer scientists has been to develop theories that capture the most relevant determinants of and thought processes leading to consumer response to novel foods. This includes nontrivial debates on how these different thought processes causally relate to each other and how we can measure this. This chapter will provide an overview of these findings' insights relevant to consumer acceptance of innovations in food.

Before we investigate consumer acceptance of food innovations, it is essential to realize that the term consumer acceptance is used somewhat ambiguously across different disciplines (Ronteltap et al., 2011). In marketing and product innovation literature, the term "acceptance of a novel product" is generally used to indicate that sufficiently many users have taken up a novel product to be profitable. Acceptance following this definition implies that a product has not only been taken up by early adopters but subsequently has been adopted by larger groups of potential users (Rogers, 1962/1995). In the literature on public understanding of science and risk analysis, "consumer acceptance" of a product or technology considers that a product is accepted if consumers have a favorable opinion about it. In these approaches, the word "acceptance" indicates that people do not categorically reject a product or technology but are in

principle willing to consider that product or technology and may even be somewhat favorable toward it (e.g., Bredahl, 2001; Siegrist, 2000). Acceptance defined as such does not imply the product is sold to anyone, let alone taken up by a larger group of users. It does predict that social protest against the innovation is unlikely and that the product has at least some chance in the market. Arguably, this latter type of psychological acceptance provides a necessary but not sufficient precondition for a product being taken up by consumers, i.e., being accepted in the other meaning of the term. In the current chapter, the emphasis leans toward the latter definition, as actual societal adoption of novel products and products still under development cannot be thoroughly studied.

The current chapter recounts current views on consumer acceptance of food innovation insights. We start this chapter by mentioning an essential shift in the 20th century when the dominance of expert and producer strategies became amended and even replaced by setting the consumer view central. Then we introduce theories on consumer acceptance and communication commonly in use in a novel food context and will list some of their limitations and ongoing developments. Subsequently, an overview of considerations when measuring consumer data is provided. Finally, conclusions about the use of consumer science in food innovation are denoted.

18.2 The emergence of consumer opinion

In the early 20th century, Henry Ford could keep it simple. The T-model Ford was said to be available in "*...any color as long as it's black.*"

Ford's strategy worked since the early 20th century can be generally characterized as a seller's market in which demand was more significant than supply. Consumers simply had to take whatever was available in the market. Around the mid-20th century, this perspective changed. The seller's market transformed into a buyer's market as the number of new products that entered the market exceeded consumer demand. Consequently, consumers turned out to be more selective in the products they bought, and sales became more important. In the post-World War II years, new products' marketing was centered around the sales function (see Solomon and Banerjee, 2006). Even though the sales (instead of the production) department was now in charge, this view still relied on the selling party's dominance. By the 1960s and 1970s, it became clear that consumers did not like to be pushed and wanted their demand more visibly reflected in products. Driven by a need for more behavioral insights about this mass consumer marketplace, it was in this period that marketing adopted a consumer orientation and started to study consumers to understand their needs and tailor products to different consumer groups (Wilkie and Moore, 2003). It became a widespread belief that companies that can uncover or even anticipate consumer demand, deliver against it, and communicate this effectively to consumers have a higher chance of survival and success in the marketplace (Costa-Font and Mossialos, 2006). Especially in the highly competitive food industry, it became critical to listen to consumers and communicate with them very carefully. Product innovation in the food industry should not merely reflect technological possibilities but also consumer needs and preferences (e.g., Van Kleef et al., 2005).

Simultaneously, risk analysis experts realized that not only did public perceptions of risk and benefits systematically differ from technical assessments (Starr, 1969), but that this also started to pose societal problems for the acceptance of new technologies. In the 1970s, research showed that people judge risks and benefits to some extent by rules of thumb rather than by making a full and deliberate assessment of the risk (Tversky and Kahneman, 1974). When measuring the perception of risks and benefits, monetary troubles were seen as more harmful than the same economic benefits as positive. With constant increases in financial risks and services, the increments of perceived risks and benefits gradually decline (prospect theory: Kahneman and Tversky, 1979). Similarly, societal risks did not follow expert risk assessment. Protests in the 1970s focused around high perceived risks of environmental pollution and nuclear power, considered to be of minor concern by experts (Fischhoff et al., 1978). This distinction between expert and lay assessment of risk was further studied in the psychometric paradigm of risk perceptions (Slovic, 1987). The psychometric paradigm explains which types of risks are systematically overestimated and what risks are systematically underestimated. It shows that risks leading to catastrophic and dreaded consequences as well as uncontrollable and unobservable risks are perceived as high from a consumer point of view, and that risk leading to nondreaded outcomes or that are controllable and observable tend to be perceived as relatively low by consumers. In the initial introduction of genetic modification, the uncontrollable and unobservable nature of genetic modification contributed to increased risk perception (Fife-Schaw and Rowe, 1996, 2000), and much less so the idea that genetic modification would lead to catastrophic problems. The psychometric paradigm and prospect theory opposed the then dominant world view that consumers can best be considered as rational decision-makers, where rational decision-makers are those who calculate and optimize the expected utility (Slovic et al., 2002; Von Neumann and Morgenstern, 1944). This worldview was challenged by the re-appreciation of emotions as not merely being epiphenomena and hindering

human functioning but instead as essential for successful human decisions-making (e.g., Damasio, 1994; Frijda, 1986). In addition, work showing the impact of unconscious (e.g., Fazio, 1990; Greenwald and Banaji, 1995) and habitual choices (e.g., Custers and Aarts, 2010; Honkanen et al., 2005) set the stage for the general realization that consumer behavior cannot be fully understood as the behavior of a rational actor.

18.3 Major approaches on consumer acceptance of innovative products

The current state of consumer research is like an "exploded confetti factory"—paraphrasing the metaphor popularized by Dutch psychologist Piet Vroon.

Consumer acceptance of innovative products has been studied using different complementary and often even contradictory approaches. Each approach is proposed or builds on theories claiming to be most relevant for the given situation and context. This may come across as bewildering to people looking at the consumer research domain for the first time, but there is some structure to it. At a higher level of aggregation, the main approaches can roughly be grouped into (1) conscious deliberation of choice models. Considerations are mostly captured in self-reports by consumers as evaluations of the innovations and intention to adopt the invention; (2) unconscious or nondeliberate choice models where consumers do not consciously deliberate yet choose an option based on intuitive, automatic, or other nondeliberate strategies; (3) behavior centric approaches where overt behavior by consumers or larger societal groups is studied without necessarily considering conscious or unconscious choices; (4) motivation central models that aim to unveil the underlying reasons why consumers would even consider the innovation at all rather than staying with current choices; (5) categorization approaches, investigating how consumers make sense of innovative products by relating them to known products, hence allowing consumers to draw inferences about properties, usefulness, and function beyond information embedded in the creative product itself; and (6) communication approaches, that aim to provide information to consumers in such a way that deliberation, motivation, behavior, and categorization follow predictable patterns. Within each group of practices, there are many different theories and methods, and some ideas and techniques are influential in more than one of these groups. But this grouping at least gives some structure to have a first glance at the consumer science domain.

18.3.1 Conscious deliberations

Conscious deliberation approaches have been, and often still are, dominant in assessing consumer responses to innovations (Ronteltap et al., 2011). By looking at deliberate consumer responses, the approach in one way or another echoes rational actor elements. This is the case for ubiquitously applied models such as the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), and its follow-up models such as UTAUT (Venkatesh et al., 2003). Similar ideas have informed studies on tailored sets of relations focusing on risk-benefit perception, trust, and knowledge (e.g., Bearth and Siegrist, 2016; Ronteltap and Van Trijp, 2007; Schenk et al., 2008; Siegrist, 2000).

18.3.1.1 Theory of Planned Behavior

The Theory of Planned Behavior (TPB) (Ajzen, 1991), the successor of the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), predicts specific consumer behavior as following from the intention of a consumer to conduct that behavior and the perceived control the consumer has about the action (Fig. 18.1). Choices are, in turn, formed

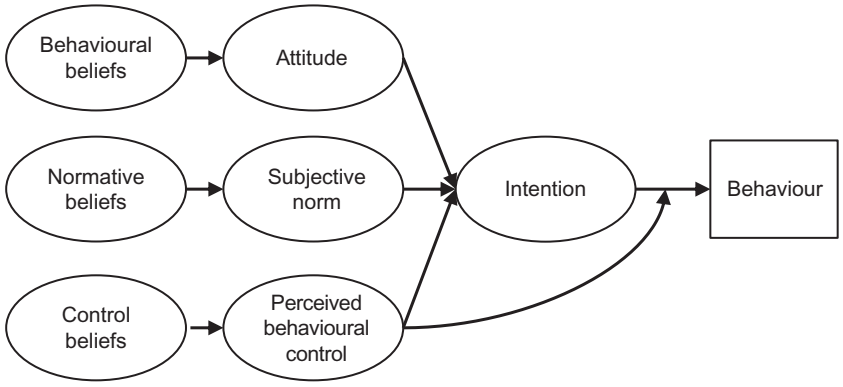

FIG. 18.1 The Theory of Planned Behavior, currently one of the most frequently applied models for predicting consumer preference formation. *Adapted from Ajzen, I. (1991). The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211.*

by attitudes, social norms, and perceived behavioral control. Attitudes are summary evaluations of the attitude object based on beliefs about how attributes of an object contribute to the overall valuation of the product and assessments of these attributes' level. Social norms are based on opinions and evaluations about social approval of conducting the behavior by relevant peers, and the perceived behavioral control results from views and assessments of the likelihood that the action is under control (Ajzen, 1991).

The Theory of Planned Behavior is among the most frequently used theories in product choice (see, e.g., Armitage and Conner, 2000) and is applied straightforwardly to novel foods (e.g., Saba and Vassallo, 2002). The theory is versatile to some extent. Additional predictors to intention, such as moral norms, have been added and were shown to be relevant in the food context (Hübner and Kaiser, 2006; Spence and Townsend, 2006). Predictors of attitude, including risk and benefit perceptions and personality characteristics (Bredahl, 2001), can be included within the framework of TPB (M. F. Chen, 2008). Moderating variables such as cross-country, occupational, or cultural differences can be used to explain different weights between norms, control, and attitude in the TPB (Chen and Li, 2007; Frewer et al., 2008).

18.3.1.2 TAM and UTAUT

The Technology Acceptance Model (TAM—Fig. 18.2) (Davis, 1989, 1993) is another frequently used model for acceptance of (technological) innovations. The Technology Acceptance Model shares many assumptions with the Theory of Planned Behavior about how consumers process information and decide. Like the Theory of Planned Behavior, it predicts the use of technology from intentions to use that technology. The purposes themselves are, in turn, indicated by the perceived usefulness and ease of technology use. The central role of ease of use and effectiveness in the technology acceptance model is related to the development of TAM to predict acceptance of home electronics. This was a topical issue in the 1980s when more complicated consumer products entered the market with often highly technical user interfaces (e.g., programmable video recorders and personal computers operating under MS-DOS[1]). Since its original conception, the Technology Acceptance Model has been modified several times into more comprehensive models. First it was extended to TAM2 (Venkatesh and Davis, 1996, 2000), including elements like social norm from TPB and elements from other models, and then into TAM3 including, e.g., computer efficacy traits of the consumer (Venkatesh and Bala, 2008). The later evolutions of the technology acceptance model were accompanied by the development of the even more comprehensive Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Venkatesh et al., 2012), which stacks up many insights from many different approaches to consumer use of technology.

18.3.1.3 Risk-benefit evaluations predicting intention

Several approaches consider the trade-offs people make about perceived negative and positive outcomes by dealing with the role of risk-benefit perceptions in consumer acceptance of innovation (Fig. 18.3). These approaches do not usually follow a predefined theoretical model but specify a specific model or set of relations to study the problem at hand. Nevertheless, there are several similarities between these approaches. Perceived risks negatively influence, and perceived benefits positively impact acceptance (e.g., Bredahl, 2001; Fischer and Frewer, 2009; Frewer et al., 2016;

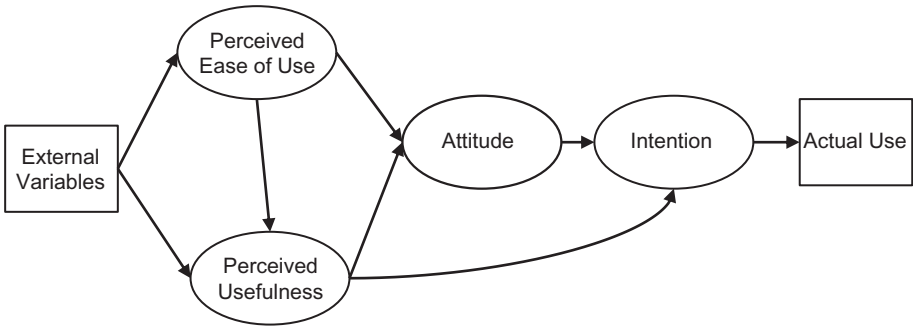

FIG. 18.2 The Technology Acceptance Model as originally proposed. *Adapted from Davis, F.D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. Int. J. Man Mach. Stud. 38 (3), 475–487. https://doi.org/10.1006/imms.1993.1022.*

[1] The late 1970s and early 1980s saw the launch of the soon dominant IBM personal computers (IBM-PC), Apple computers and home computers (such as the Commodore 64 and Sinclair ZX80), which used text-based programming languages such as MS-DOS that were introduced in 1981. The need for user oriented computer interfaces was recognized early by Xerox who developed a graphical user interface (GUI) for its Alto computers (1973) and Xerox Star (1981). The uptake of these ideas in the Apple Macintosh (1984) and the launch of Microsoft Windows 3.1 (1990) for computers heralded a shift from syntax-based to graphical user interfaces that to date dominate consumer computers.

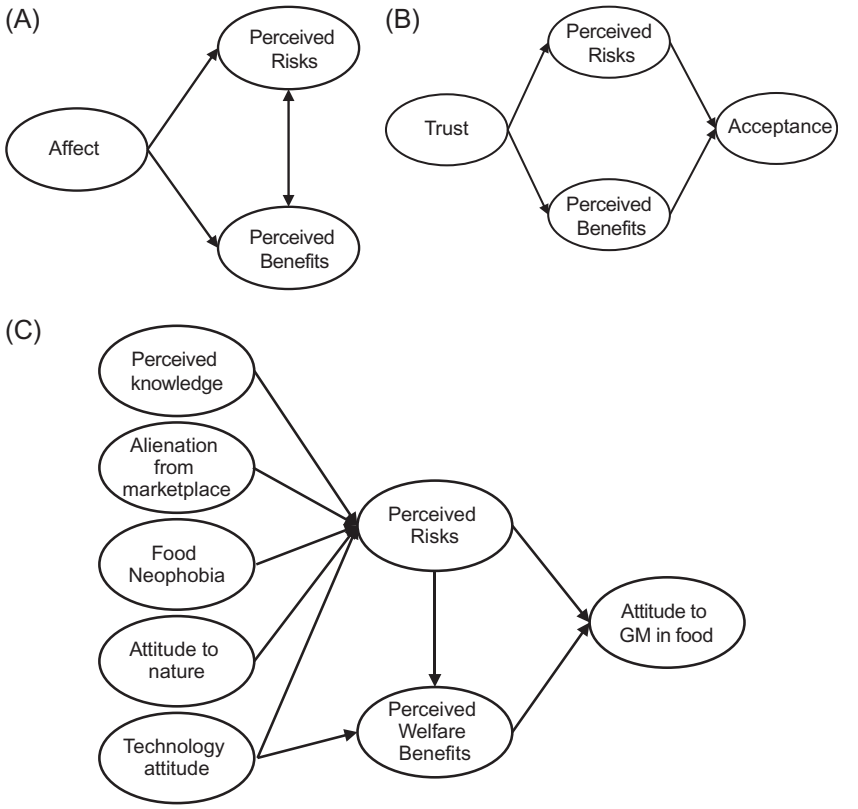

FIG. 18.3 Examples of risk-benefit models. (A): (Finucane et al., 2000), (B): (Siegrist, 2000), (C): (Bredahl, 2001). Note that these are only a few examples of this kind.

Schenk et al., 2008; Siegrist, 2000; Siegrist et al., 2007). Following from prospect theory (Kahneman and Tversky, 1979), it has been often assumed that if risks (or losses) loom larger, then perceived risks should overwhelm the benefits. In the adoption of food innovations, there is, however, little evidence for this idea (see, e.g., Fischer and Frewer, 2009; van Dijk et al., 2012; van Dijk et al., 2017). In fact, a meta-analysis across innovation acceptances beyond food shows that in about one-third of the cases, benefits weigh more, in about one-third risks, and in the rest, it is too close to call (Bearth and Siegrist, 2016). What exactly determines whether risk or benefit weighs heavier is not yet clear. To some extent, this may depend on different types of risks and benefits playing a role. For example, when comparing personal risk to societal benefit, risks may weigh heavier (Schenk et al., 2008), while when comparing privacy risk to health benefit, the health benefits may outweigh the risks (Berezowska et al., 2015). It is frequently found that consumers consider products they perceive as high in risk to be low in benefit (and vice versa). Empirically, this is shown by the negative correlation between risk and benefit perceptions (Alhakami and Slovic, 1994; Finucane et al., 2000; Siegrist et al., 2007). This relation, called the affect heuristic, is explained by an underlying effect or feeling causing both risk and benefit perceptions (see Fig. 18.3A Finucane et al., 2000). While this negative correlation is often not very large (see, e.g., Fischer and Frewer, 2008), it is striking nonetheless as we would expect that viable innovations would avoid low-benefit high-risk products and instead only develop high-risk products that are also offset by high benefits.

Besides focusing on risk and benefit perception in isolation, different antecedents of risk and benefit perceptions have been studied. In the early 2000s, trust in the agent, producer, or government that launches or communicates about innovation was seen as a critical predictor of risk and benefit perception (Frewer et al., 2016). A high level of trust was considered to have a significant effect on reducing risk perception and increasing benefit perception (Frewer et al., 2003; Siegrist, 2000) (see Fig. 18.3B). Trust, however, as a predictor was shown to be more complicated. Several studies indicated a reversed causality where we trust those who tell us what we want to hear. In other words, our acceptance of technology causes us to trust those who communicate according to our own opinion (Eiser et al., 2002; Poortinga and Pidgeon, 2005). This implies that creating trust is not always possible, nor may it be the silver bullet for reducing risk perception. Besides belief, many other antecedents of perceived risks and benefits, including objective or self-experienced knowledge levels, neophobia, and general attitudes toward nature and technology, have been conceptualized and empirically tested (see Fig. 18.3C), and more ideas have been developed to date, as illustrated by the increasing number of determinants for technology acceptance studied over the years (Gupta et al., 2012).

18.3.1.4 Limits to conscious deliberation models

"History warns us … that it is the customary fate of new truths to begin as heresies and to end as superstitions." ***Thomas Henry Huxley, Collected Essays Of Thomas Henry Huxley***

TPB, TAM, and the risk-benefit approaches all assume that consumers analyze information about specific attributes of a product or technology. After such conscious deliberation, consumers are assumed to be aware of their rationale, and the self-reported attitude or acceptance is considered to be the most relevant predictor of behavior. It has become the common ground to challenge the idea of the consumers as rational actors. Supporters of the above models will claim their approaches are not rational actor models. Through their deliberative evaluations, they nevertheless remain heavily informed by the rational actor model, which through these echoes remains influential in consumer behavior research.

Challenging these models and their underlying assumptions is the fact that the predictive values of self-reported attitudes on behavior are often low (see, e.g., Armitage and Conner, 2000; Van Dam and Fischer, 2015). This intention-behavior gap can, to some extent, be attributed to methodological and/or conceptual limitations of the reported studies. It has been shown that intention-behavior gaps become more problematic if the behavior is measured at a different level than the self-reported measure, i.e., if the correspondence between perceptions-attitudes-intentions and behavior is low (Fishbein and Ajzen, 1975). For example, pro-environmental behavior is often measured as purchasing specific products, while the measured consumer opinion is about ecological behavior or even personal values aimed at sustainability in general. This part of the problem can be solved by measuring beliefs, intentions, and attitudes at the same (preferably) concrete level as the behavior (Kaiser, 1998). In general, it is therefore essential to ensure that the specificity of actions and opinions closely correspond when designing a survey (Oppenheim, 2000). Another often ignored issue is that consumers will deliberate when filling out surveys and do so with another task set in mind than when they have to choose in a real situation. When filling out surveys, people may be more tuned into their ideal state of the world, looking at desirabilities. At the same time, when forced to make decisions in a retail setting, they may have to look at the available options they have, the feasibilities (e.g., van Trijp, 2014), including limited time and fatigue in making decisions.

Another critical note to deliberate choice models is that they tend to grow over time. Increasingly, many determinants and other variables of relevance have been identified over the last decades, without previous ones being discarded (Gupta et al., 2012). Some of the progress in deliberate consumer models is based on the addition of such predictors. Examples are the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2012) as well as the evolution of the original Technology Acceptance Model (TAM). The UTAUT is currently one of the most comprehensive models around and includes many constructs. While such a complete model (necessarily) better describes collected data (high explained variance), it also results in a complex model, making it hard to make predictions about an innovation's success. In addition, much of the additional explained variance from the added predictors may introduce statistically significant, yet real-world irrelevant effects (Cohen, 1992a; Lynch Jr et al., 2012). Adding more variables may even distract us from the more critical problem that many of the central psychological processes in consumer decision-making remain largely unexplained (Bagozzi, 2007). In other words, by introducing such comprehensive approaches, we may have sacrificed understanding of what is going on, may have lost focus, and may ultimately not be better off but be even worse off in predicting future situations compared to simpler models. Most progress could probably be made by better understanding and revising the core of consumer decision-making insights, rather than by adding ever more detailed determinants to existing models.

18.3.2 Unconscious or nondeliberate choice models

18.3.2.1 Distinction between two systems of consumer choice

Over the last decades, general agreement has grown that humans can combine information and make decisions in two different ways, either in an effortful way that more or less follows a computational weighing of perceptions or in a way that requires little effort (Kahneman, 2003). Such a low step, the heuristic system takes care of most decisions and ensures that mind power remains available for more complex tasks (as already realized by James, 1890/1950, p. 122). Consider, for example, how incredibly tiring it would be to have to think through every step you take when walking down the corridor. This automatic, system 1, depends on automatic activation of thought and behavior, which limits it to a range of predefined responses and makes it susceptible to signals from the environment. These limitations of system 1 may lead to suboptimal behavior from time to time. A second system is more reflective and is called upon when the first system cannot deal with the situation. But involving this dual thought system comes at the cost of spending

more mental effort (Kahneman, 2003). System 1 is the default system, and whether system 2 pitches in is both context- and situation-dependent. This context dependency may be another reason for seemingly inconsistent consumer behavior. However, much of system 2 plays a role; the default status of system 1 makes its inclusion into consumer response models necessary in the context of novel foods. Particularly for foods, it is unlikely for people to elaborate on their decisions, at least not at all moments. Many food choices are frequent and habitual, and spending time and motivation to think through all options all the time seems excessive. Moreover, consumer response to new technologies is deeply embedded in a cultural context with corresponding (unconscious) intuitions and associations, which can be more easily understood from system 1 than a system 2 approach. Even completely new technologies are still likely to activate all kinds of associations, relevant or irrelevant, positive or negative, if only because there is some general food technophobia (Cox and Evans, 2008) or a feeling of uncertainty that in itself may be felt as unpleasant (Fischer et al., 2013).

18.3.2.2 Implicit attitudes and affective responses

Strong existing associations may lead to a first unconscious gut response (Haidt, 2001). Such first implicit associations are often unconscious and may contradict self-stated attitudes (Greenwald and Banaji, 1995; Fazio and Olson, 2003). In some situations, self-stated attitudes may even be subjected to such implicit associations (Gawronski and Bodenhausen, 2006, 2011), which raises the question of whether implicit associations, self-reported judgment, or a mix of these represent the most relevant consumer opinion (Gawronski, 2007; Gawronski and Bodenhausen, 2006). Generally, it is assumed that the less time and effort available for a decision, the more the behavior is determined by implicit associations (Greenwald et al., 2009). In the context of consumer food choice, implicit associations and self-stated attitudes tend to correlate positively (Hofmann et al., 2005), and self-stated attitudes tend to relate more clearly to behavioral choices (Greenwald et al., 2009). It is, however, unclear whether this is because of the noisiness of implicit measures (Lebel and Paunonen, 2011) or something particular for food innovations. For example, there are indications that categorizing cultured meat as meat replacement can cause contrasting implicit associations and self-stated attitudes (Bekker et al., 2021). Others argue that implicit associations and explicit attitudes interact (Gawronski and Bodenhausen, 2006). In the context of new food technologies, this view was supported by Spence and Townsend (2007) and Richetin et al. (2007). They found that explicit attitudes and implicit attitudes both contributed to understanding consumer decision-making.

Besides implicit, intuitive associations that a novel food or technology may trigger, it is also the case that in complex situations with insufficient knowledge, people often rely on simple cues to make decisions about risks and benefits (Siegrist and Cvetkovich, 2000; Siegrist and Hartmann, 2020). An increasing number of studies found that feelings associated with new food technology impacted its acceptance (Siegrist and Sütterlin, 2016; Siegrist et al., 2018). This is the kind of decision-making for which Finucane and colleagues used the term "affect heuristic" (Finucane et al., 2000; Slovic et al., 2004), which postulates that the effect associated with an object, such as a new food product, impacts perceptions and evaluations of that object. Most of the studies that have examined the impact of the affect heuristic on the acceptance of new food technologies have focused on general effects, ranging from negative to positive. The emotion literature distinguishes emotions beyond positive and negative (Ekman, 1992; Russell, 1980) and assigns specific functions to specific emotions (Oatley and Johnson-Laird, 1996). One such specific emotion is disgust, which is enjoying increasing interest concerning novel foods and can be viewed as a particular case of the affect heuristic. Studies have shown that evoked disgust influences the acceptance of genetically modified food (Scott et al., 2016) and other novel food technologies (Egolf et al., 2019). Similarly, naturalness perceptions play an important role in accepting new food products (Román et al., 2017; Siegrist and Sütterlin, 2017). Naturalness evokes almost exclusively positive emotions, and relying on the natural-is-better heuristic leads to a negative tendency in decision-making related to novel foods (Fischer et al., 2013; Siegrist and Hartmann, 2020).

18.3.2.3 Habits and routines

Habits in consumer choices have been both praised and lamented. Habits and routines allow consumers to conduct well-known practices that have been learned in an intuitive way (Aarts and Dijksterhuis, 2000b). The automatic goal pursuit following from habits and the associated routines (Aarts and Dijksterhuis, 2000a) is very efficient for such common tasks, a fact already observed in the late 19th century: "*the more of the details of our daily life we can hand over to the effortless custody of automatism, the more our higher powers of mind will be set free for their own proper work*." (James, 1890/1950, p. 122). Good habits have, for example, been shown to support safe food preparation (Fischer and Frewer, 2008).

Habits and routines are not infallible, though. Most of us can recall cases when going to a shop to get that special new and innovative product, only to realize on returning home that you forgot the product for which you went out and that you instead returned with the usual daily groceries. The established routine or script is started for all the good reasons, i.e., being efficient in getting to the shop. The problem is that once the automatic script takes over, the

interruption signal to stop the script at the appropriate time to allow you to pick up the special product tends to fail. The script continues shopping for usual groceries and returning home, leading to unwanted behavior (Reason, 1990). This can be remedied by prompting people to make new choices when the script should be interrupted. This way, habits and more deliberate choices can intermix successfully (Adamowicz and Swait, 2013), but having that prompt in place is not trivial.

In many cases, habits and scripts are considered to be outright counterproductive. Especially in dieting behavior, snacking, or otherwise, unhealthy food intake habits are seen as a major problem (e.g., Verplanken and Faes, 1999). Insights from psychotherapy suggest that to change habits, different techniques, based on different theories, applied to different stages in the change of a habit are probably most successful (Velicer et al., 1996). This trans-theoretical approach has been applied with some limited success in the context of healthy eating (De Vet et al., 2005).

More recently, habits, routines, and scripts are interpreted in lifestyles (Montero-Vicente et al., 2019), which suggests that to change or improve habits a better understanding of the lifestyle of consumers is useful.

18.3.2.4 Limits to unconscious choice models

While it is easy to consider unconscious choice models in terms of two distinct processes, there are problems with that approach. The delineations are, however, far from trivial. Some researchers, for example, list emotions with the unconscious system (e.g., Kahneman, 2011), while emotions may also have a more conscious and deliberate function (e.g., Frijda, 1986; van Giesen et al., 2016). Besides emotions, the unconscious system also has to accommodate the equally unconscious habits, routines, scripts, heuristics, and in extremis reflexes we apply. Understanding this unconscious system or these unconscious systems is lagging considerably (Glöckner and Witteman, 2010). It is probably the bag of tricks buried in our automatic systems that makes for human intelligence (Dennett, 1995), but the structure, whether it is one or multiple systems, and how these interact is not yet clear. Conscious and deliberate consumer choices, perceptions, and deliberations can be measured at good face validity. With unconscious measures, this is less clear. To what extent do time-based categorization tasks (Greenwald et al., 2009) or response times after being primed (Fazio and Olson, 2003) indicate an unconscious opinion? How to interpret response time differences when confronted with new objects (Bekker et al., 2017; Bekker et al., 2021)? To what extent does stress imply an opinion or something else? Where in the brain are our opinions located? Many of these questions remain unanswered.

At a more practical level, consumer decisions from the unconscious and the deliberate system are often aligned for consumer products (Greenwald et al., 2009; Hofmann et al., 2005). This means that for many mundane food decisions, it does not matter how consumers express their attitude as it will be similar anyway. For many practical purposes, it will thus not matter much whether we (cheaply) ask people for their conscious opinion or put effort into understanding their complicated unconsciousness.

18.3.3 Behavior central models

18.3.3.1 Context-based goal behavior—Nudging

It is now generally accepted that goals can be automatically and unconsciously activated (Custers and Aarts, 2010), attitudes can be implicit (Greenwald and Banaji, 1995), and decisions can be made based on heuristics (Kahneman, 2003). This makes triggering relevant goals, attitudes, and decisions seem an obvious approach. This can be achieved to some extent by changing the environment in which the consumer behaves. This is the approach introduced as nudging (Thaler and Sunstein, 2008). More specifically, it was claimed that by making specific changes in the choice architecture (i.e., the environmental context consumers have to make decisions in), consumers could be unconsciously steered toward an optimal choice for their unconscious goals and demands. These environmental interventions rely on human decision biases, such as status quo and default bias, loss aversion, and others (Galizzi, 2014). Nudging takes a lot of the decisions out of the consumers' hand and puts them in the hands of the designer of the choice environment. The number of nudging intervention studies in a food context is increasing, especially with regard to steering consumers toward healthier food choices (Vecchio and Cavallo, 2019; Wilson et al., 2016), but more recently also in the context of stimulating novel foods, such as novel plant-based dishes (Zhou et al., 2019). Nevertheless, there is still a strong need to further validate the nudging potential in the context of consumer acceptance of novel foods.

18.3.3.2 Lead users' approaches

Consumers that make automatic and habitual choices do so based on a vast amount of prior experience and preference. If innovative products and technologies can be developed based on this vast amount of consumer knowledge and their use in daily life, the likelihood of successful introduction increases (Von Hippel, 1976), even without the need

to change attitudes. This requires a reversal in communication, i.e., rather than innovators communicating their plans to end-users, end-users now need to communicate and be involved as stakeholders early in the development of new technology or product embodying it to capture a more usage-driven view into the development process itself (von Hippel, 1986). Bringing consumers into innovation teams as stakeholders is claimed to be a way to allow usage of end-user evaluations early in development, which limits the number of adjustments that have to be made after the development stage (Nahuis et al., 2012). Consumer involvement in designing new food products has been the focus of consumer research (Banović et al., 2016; Busse and Siebert, 2018; Filieri, 2013; Moskowitz et al., 2006). Early end-user involvement seems promising and recent research shows that marketing products as cocreated positively affect consumers' perceptions of new food products (Jacobsen et al., 2020; Nishikawa et al., 2017). Strong empirical evidence that this approach does indeed lead to fewer failed products and technologies is lacking (Reinders et al., 2013). In addition, best practice is hard to identify, as this often involves a considerable change in the structure of the innovation process. When adopting a consumer involvement approach, the classical cascade method, where technology is developed first before product and market introduction, cannot be maintained. Instead, at each moment of technology development, insights from markets and end-consumers need to be fed back into the innovation process. This requires advanced methods to tap into consumer opinions while developing a product or technology (Granato et al., 2021). At the same time, it requires that the innovation process is receptive to this information from consumers. This can only be achieved if the approaches are fully embedded in the organization, including in the code of conduct, employee reward schemes, and top-level management support (Munksgaard and Freytag, 2011; Rossi, 2011).

18.3.3.3 Societal adoption

Most of the theories on consumer acceptance of innovation focus on individual consumers, either from a psychological point of view, as in the theory of planned behavior, or as a lead user who influences others. Another approach to acceptance of innovation takes the position that innovation is only truly accepted when an influential group or even the entire society adopts it in. This shifts the focus from the more psychologically based outlooks considered so far to a more sociological approach. The best-known approach is diffusion of innovations as developed by rural sociologist Everett Rogers in the early 1960s (1962/1995). Originating in agriculture, his approach has been widely used to study the diffusion of innovations, including food innovations. The diffusion of innovations has maintained its original ideas with relatively little change since the 1960s. It assumes a sequence of uptake in society, where a small proportion of innovators (about 2.5%) are the first users of technology. These innovators may be intrinsically inspired by the novelty of the innovation and forgiving of teething pains and high prices. The next group consists of early adopters (13.5%) who are among the first to use the mature product. This is the moment where an innovation diffusion is starting to gain speed and where it may be able to independently take off (Janzen et al., 2009) or where it may fail. In the early majority stage (34% of use), the product growth tops out, and diffusion speed reduces in the late majority (34%) and laggard phases (16%) when the market becomes saturated at the innovation's most widespread use. The emergence and reduction of the different consumer segments of innovators, early adopters, majorities, and laggards were modeled in more detail in the late 1960s (Bass, 1969), and this "Bass model" has become a central feature of the diffusion of innovation approach. In addition to modeling the road to market saturation of innovations, diffusion of innovations research has identified five generic characteristics of innovations that have been successfully adopted in the market. Successful innovations generally have (a) relative advantage (i.e., delivering a benefit over preceding technologies), (b) compatibility (i.e., fitting with values, experiences, and needs of potential adopters), (c) complexity (i.e., level of ease of use), (d) trialability (i.e., the possibility to experiment with an innovation before actual adoption), and (e) observability by others.

18.3.3.4 Limits to behavior central models

Although the use of environmental interventions seems to be a promising avenue for increasing consumer acceptance of novel food products, several caveats occur for this approach (de Wijk et al., 2016). One of the most acknowledged limitations of using nudges or similar interventions is the duration of their effectiveness. Scholars argue that nudges might have only a short-term effect and studies very rarely are capable of evaluating the long-term outcomes of these type of interventions (Allcott and Rogers, 2014; Bucher et al., 2016; Vecchio and Cavallo, 2019). In addition, the external validity of many nudging studies is relatively low. For example, many studies are characterized by small and nonrepresentative samples, and contexts are selected on a pragmatic basis. Future research should aim to collect a greater diversity and amount of consumer data in different settings to improve further evidence from this type of intervention (Vecchio and Cavallo, 2019). Finally, from a more ethical perspective, these types of interventions are debatable as they affect the autonomy of individuals, especially when they are applied in the context of vulnerable groups.

Lead-user approaches also suffer from some limitations. As incremental innovations and minor product modifications generally dominate the food industry, most product concepts that are currently codeveloped with consumers are not radically new. However, for more radical new product ideas, consumers are assumed to bring forward ideas of products and concepts with which they have no first-hand experience. Lack of experience and foresight, as well as consumers' inability to express their needs and recall the problems they encountered, limits effects of real-world experiences. As a consquence, end-user participants tend to come up with incremental rather than radical new product ideas (Greer and Lei, 2012; Moskowitz and Hartmann, 2008). A quote attributed to Henry Ford illustrates this: "*If I had asked people what they wanted, they would have said faster horses*." In addition, the complexity that codevelopment activities bring along with the required participant skills, especially in contexts with high technical sophistication, may further hamper the success of this approach.

The diffusion of innovations approach has been very successful in the 60 years of its existence to describe how innovations (failed to) diffuse in society. However, it can only define market saturation after the last laggards have accepted an innovation, making its predictive power limited. The total amount of purchased products based on an innovation determines when the market is saturated and hence the total number of consumers buying into the innovation. This number is smaller than the general population (not everyone will buy pedelecs, for example), but the number remains unknown until the market is saturated. This means that we cannot use the percentages defined in the Bass curves to predict the number of adopters, but merely to describe them once the innovation has diffused. A similar problem occurs with the preconditions for acceptance (advantage, compatibility, complexity, trialability, and observability) that often can only be determined once the innovation has diffused. The lack of insight into psychological deliberations leading to consumers objecting to or favoring innovation in the diffusion of innovation model (Claudy et al., 2015) hence makes it a more descriptive, but less useful, predictive approach.

18.3.4 Motivation central models

18.3.4.1 Motivation to approach or to avoid

Due to two fundamental human tendencies, i.e., neophobia (i.e., the fear of novelty) and neophilia (i.e., the urge toward novelty), individuals are alternating between approach (neophilia) and avoidance (neophobia) reactions toward new food products (van Trijp and van Kleef, 2008). This motivation to approach or to avoid innovations aligns with the Health Belief Model introduced in the 1950s (Janz and Becker, 1984), which focuses on motivations why and when perceived threats to personal health result in consumer behavior aimed at avoiding or nullifying those threats. Similarly, the Protection Motivation Theory (Rogers, 1983) introduces two ways of dealing with potentially harmful situations. The first route (labeled maladaptive) is based on avoiding threats, while the second route (adaptive) is about coping with threats. If a threat is appraised as substantial and copying is considered feasible, the motivation to engage in protective behavior is strong, and action to deal with the threat is likely. From the perspective of innovations, it should, however, be noted that this model focuses more on removing potentially negative consequences of a situation and how to deal with these than on specific properties of the product or innovation.

Furthermore, in this context, one type of motivation that has received much attention is that of regulatory focus (Higgins, 2000). The motivation may either be to avoid negative consequences or to approach positive consequences (Carver and Scheier, 1998). While both motivations may push toward the same optimal state, it has been shown that people in a prevention mindset are more likely to choose products that facilitate avoiding negative consequences, while people in a promotion mindset choose products that help them get closer to their goal, i.e., there is a regulatory fit (Higgins and Scholer, 2009). For food innovations, this may be of relevance when considering to communicate about avoiding risks or gaining novel benefits. Preliminary evidence showed that when there was a fit between a consumer's regulatory focus (i.e., promotion vs prevention mindset) and the framing of a message (i.e., stressing the attainment of positive outcomes or the prevention of negative outcomes), more positive attitudes and a greater willingness to buy GM foods can be accomplished (Fransen et al., 2010).

18.3.4.2 Context-based goals—Construal level

Consumers are sometimes depicted as inconsistent. However, a person may adopt a specific consumer role with different associated goals and motivations and hence shows seemingly incompatible behavior compared to the same person who acts in the role of a responsible citizen (Johnston, 2008). This includes the case where people are negative, e.g., about GM food, but still consume it, and in cases where people are positive but do not buy it (e.g., organic produce Vermeir and Verbeke, 2006). Such seeming inconsistencies in behavior may be due to the fact that

people can construe meaning to food products interchangeably at a high level or a low level. The high level is characterized by value relevance and is abstract. Long-term consequences, socially and geographically distant effects, as well as hypothetical uncertainties all fit with a high construal level (Trope and Liberman, 2010). A low construal level is more related to immediate, personally relevant, local effects that are certain and concrete. High construal levels may be more connected to the citizen role of people, and the way people fill out questionnaires, while consumers having to buy a food product right now are more likely to make these choices based on low construal level (Van Trijp and Fischer, 2011). For innovations, it is essential to realize that discussing a future, uncertain technology as a whole (high construal) may result in answers more related to a citizen than a consumer. Construal level theory has been applied with some success in adopting new, somewhat risky behaviors. People confronted with psychologically distant risks are less likely to perceive these risks as high (Zwickle and Wilson, 2013), and hence people are assumed to be more likely to adopt risky behavior when chances are at a higher, more abstract, or more distant level (Trope and Liberman, 2010). The evidence that risks perceived as closer indeed reduce adoption behavior (Schuldt et al., 2018) and was, for example, shown for the use of nanotechnology in orange juice production (far away), packaging (closer), and nutritional enhancements (very close, Steenis and Fischer, 2016). This suggests that close and immediate risks are more likely to influence behavior (Nussbaum et al., 2003). For benefits, the argument is less clear. It has been argued that for any risky behavior to be even considered, there should be a benefit. Hence it has been argued that benefits are superordinate to risks and therefore construed at a higher, more abstract level (Eyal et al., 2004; Herzog et al., 2007; Trope and Liberman, 2010). Against this, there is evidence that the construal level of benefits does not matter much (Steenis and Fischer, 2016) or even that concrete and tangible end-user benefits, i.e., psychologically close benefits, are essential for action (Van Dam and Fischer, 2015). While this points at both the versatility of explaining observations using the construal level theory, it also points at its main weakness. It is almost always possible to interpret results in the context of construal level theory, but it is often hard to make unambiguous predictions based on the theory. Whatever the case, one important message is that construal level theory suggests a fundamental asymmetry in how consumers deal with risks and benefits beyond that suggested in the prospect theory (Kahneman and Tversky, 1979). We should hence carefully reconsider outcomes of studies framing benefits of an innovation merely as the removal of risk instead of as adding intrinsic value (Berezowska et al., 2018).

18.3.5 Categorization approaches

All the above models take the approach that information about a novel product or technology is processed in the mind leading to an opinion about that product. An alternative to the assumption that beliefs are based on a systematic combination of arguments is that already present opinions of similar products are used as an indication for evaluation of the innovative product. This allows consumers to predict the attributes of a product based on their knowledge of products in the same category. Categorization literature in marketing shows how people assign new products to existing categories (Loken, 2006); how these categories may need to be adjusted to accommodate the innovative product (Moreau et al., 2001), or when a new class has to be created to give the innovative product a place in the mind (Michaut, 2004). In this respect, previous literature shows that the level of congruity between a novel product and an existing knowledge structure influences the nature of information processing and therefore affects the innovation-decision process. Consumers evaluate moderately incongruent new products more positively than congruent or extremely incongruent ones (Mandler, 1982; Meyers-Levy and Tybout, 1989). An innovation that is too similar to (congruent with) existing product categories will not evoke much interest, while an innovation with extreme, unmanageable incongruity requires too much cognitive elaboration and will be evaluated negatively. In contrast, new products that are moderately incongruent with existing product categories are most likely to be regarded as "interesting and positively valued" (Meyers-Levy and Tybout, 1989). This kind of thinking can also be found in many contemporary design principles, for example "Most Advanced Yet Acceptable (MAYA)." Using MAYA, Raymond Loewy stated that users should be presented the most advanced design, but not more advanced than what they were able to accept and embrace.

In addition, this stream of literature studied how communication can facilitate placement of innovative products into relevant categories by creating analogies between the novel product and existing categories (Gregan-Paxton et al., 2002; Gregan-Paxton and John, 1997), and how this leads to opinions about and acceptance of the innovative product (Kardes et al., 2004; Sujan, 1985). Going one step further is using experiential analogies in which a novel product is compared to an emotional experience (Goode et al., 2010). Such an analogy has the power to focus consumers on the evaluative, emotional, and multisensory information associated with the product experience and could especially have the potential to enhance the acceptance of novel products within the food domain. However, in spite of the

potential contribution to understanding consumer acceptance of innovations, the research into category-based inferences has not customarily been used in the literature on consumer response to innovation. It has developed in different scientific communities and with other jargon (Ranganath et al., 2010).

18.3.6 Communication of new technologies

18.3.6.1 Communication to change evaluations

"The single biggest problem in communication is the illusion that it has taken place." ***George Bernard Shaw***

What many approaches predicting consumer response to innovative products have in common is that evaluations of the innovative product and its attributes lead to perceptions or attitudes. Positive attitudes, in turn, lead to positive responses and more consumers buying the product. These models tend to be linear, as in that they start with the construction of perceptions and attitudes and end with behavior. Under this assumption, influencing consumer perceptions and attitudes will lead to predictable behavior change. The obvious choice is to influence attitude by providing additional information about the properties of the innovative products so that an attitude is formed based on complete information on the innovation. This will only work, however, if we know to what extent the information is indeed communicated.

One of the leading models in this context is the elaboration likelihood model (ELM) (Petty and Cacioppo, 1986). The elaboration likelihood model posits that communication can be interpreted and processed in two different ways by consumers. From the communication perspective, the central route (as labeled by Petty & Cacioppo) is the most desirable one, leading to an elaborate and systematic use of the provided information resulting in a lasting and predictable change in attitudes in the direction of the provided information. The central route is, however, very demanding on consumers, as it requires that (Petty and Wegener, 1999):

(a). consumers are motivated actually to use the information (e.g., because it is personally important to them);
(b). they are able to process information at the time it is provided (are not distracted, information and jargon fit in with their knowledge);
(c). the information is given at sufficient quality and adds to existing knowledge; and
(d). people take the time to repeat the information in their mind and memorize the information.

If any of these conditions are not met, people will either maintain their existing attitude or will temporarily change their opinion based on using the other peripheral route to process the communicated information. Peripheral cues may be specific words or may even be associations at the periphery of the message, e.g., the layout, paper quality, and color scheme of a leaflet.

Other models of attitude change take this thought one step further and posit that as long as people think they have sufficient knowledge, they will not consider new arguments at all (Heuristic Systematic Model Chaiken, 1980; Chen and Chaiken, 1999). The Risk Information Seeking and Processing Model (RISP) follows this latter idea by positing that it is the perceived lack of information that is the consumers' main driver for seeking and using information about a product or situation (Griffin et al., 1999; Griffin et al., 2002; Trumbo, 2002; Yang et al., 2014).

To systematically and centrally process the content of the communication, the consumer has to consider the information as relevant, is willing to spend time and effort, as well as has sufficient knowledge and intelligence to process the information. If any of these preconditions are not present, no predictable lasting change in consumer opinion will result. Ideally, we would therefore ensure that consumers are highly motivated to choose the best food products available in order to make them useful information to the fullest extent. Motivating consumers to think about food choices may, however, not be successful as food choices are persistent (most of us make multiple food decisions every single day). Therefore considering each food decision in detail would quickly become overly demanding.

18.3.6.2 Communication affecting behavior in a noncentral way

"The biggest problem is not to let people accept new ideas, but to let them forget the old ones." ***John Maynard Keynes***

If we consider the sheer amount of time needed to elaborate on each single food decision we take, it makes sense that many, if not most, of our food decisions are based on heuristics, habits, and past behavior (Honkanen et al., 2005).

Communication messages are unlikely to directly influence habits, as habits tend to be stable and hard to change, as many have experienced when forced to abandon the long-established handshaking habit during the 2020 COVID-19 pandemic. To change habits, it is first necessary to be aware that current habits are a problem, and only then is an individual likely to engage in stages of changing behavior and adopting new habits (Prochaska and DiClemente, 1983; Velicer et al., 1999). Habits are often associated with behavioral scripts. Once a habit is activated, a consumer adopts a sequence of automatic, habitual actions without further conscious control. These scripts may take over conscious decisions: who has not experienced something similar to going to the kitchen to pick up a specially bought treat only to return with the habitual glass of water instead? Habits often link to underlying associated goals (Custers and Aarts, 2010); hence activating a relevant habit may, in fact, be sufficient communication at some moments: a nudging approach.

Another way to capitalize on the noncentral processing of information is by the use of framing. The same information content may result in a different evaluation regarding how it is communicated (Kahneman and Tversky, 1984). Probably the most well-known example is the presentation of a glass as either half-full or half-empty. But also, the mere expression of numbers as fractions or percentages compared to natural numbers may lead to different interpretations of the same results (Gigerenzer and Todd, 1999). Framing can be used in a broader, more qualitative sense to discuss innovation trajectories, approaches, stakeholder inputs, and resulting outcomes in different ways (Zwartkruis et al., 2012).

Once accepted that the way in which we communicate could influence the underlying psychological processes, the link with the models from the previous sections seems obvious. In communication literature, the focus in these cases is often in establishing a fit between the message and the assumed process. For example, a benefit message is likely to resonate better for people who have an (induced or trait-wise) approach motivation, while information about immediate effects is likely to be more relevant for consumers asked to chase low construal goals (Berezowska et al., 2018). While many insights are increasingly gathered on these nonsystematic effects, the knowledge remains scattered, and a systematic framework to capture all effects remains required (Glöckner and Witteman, 2010). Until that time, consumer researchers may have to search and test for the most relevant communication approach in any given situation (Berezowska et al., 2018).

18.3.6.3 Social media communication and online WOM

Social contagion processes play an essential role in the diffusion of product innovations. A central role in these social contagion processes is reserved for word of mouth (Arndt, 1968). Especially for innovations, interpersonal communications stimulate adoption of new products (Gatignon and Robertson, 1986; Midgley and Dowling, 1993; Van den Bulte and Lilien, 2001) and hence are extremely important to the speed of the diffusion process in a social system (Mahajan et al., 1990). Early marketing research already revealed that consumers tend to turn to friends and significant others for advice and information (Childers, 1986; Czepiel, 1974). Information acquisition by means of word-of-mouth or interpersonal communications accomplishes the formation and change of a consumer's attitudes and subsequent behavior (Brown and Reingen, 1987). More specifically, word-of-mouth information has been shown to play an essential role in relieving uncertainty (Murray, 1991; Price and Feick, 1984). Interpersonal communications have more effect in reducing consumer's risk perceptions than mass media communications because people can ask for clarification and get direct feedback on their questions (Murray, 1991). Recently, this consumer advocacy for new products and brands has moved from an offline to an online environment (Eisingerich et al., 2015). The Internet has changed the form and definition of word of mouth, which is no longer limited to face-to-face contact. Online word of mouth (WOM) can be defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al., 2004). Online WOM has been proven to be a significant influencer of consumers' decision-making regarding companies and brands (Jin and Phua, 2014). As a particular form of online WOM, social media and social networks have become prominent sources of information and means of communication on food (Fleming-Milici and Harris, 2020; Simeone and Scarpato, 2020) and normative influence (Hawkins et al., 2020). That social media does not always provide a positive contribution to food consumption behavior is shown by Simeone and Scarpato (2020) who found that the quality of information on social media is often low and that social networks tend to homogenize consumption, and not always in the 'right' direction. Nevertheless, despite these findings, research on the role of social media in the uptake of novel foods is still in its infancy and appears to be an interesting direction for research in the near future.

In summary, there is a broad range of approaches to assess consumer response to innovations and how to communicate with consumers, both within consumer psychology and beyond. All presented methods model consumer responses. Modeling implies that we are talking about simplified reflections of reality and that many important determinants of behavior are left out. The specific question one has and the decision which indicators of consumer response

are most essential to know at which stage of the innovation development process should be used to select, adapt, and apply the most relevant approach. This decision should be taken consciously and re-evaluated frequently; and ever so subtly, different approaches may require the choice of other theories. New insights may lead to the evolution or even rejection of established theories, making a well-justified and confident choice from this myriad of options a hallmark of an expert consumer researcher.

18.4 Methodologies to record consumer opinions on novel foods

"Never used it myself,' Ridcully said. 'Wetting a finger and holding it up has always been good enough for me." ***Terry Pratchett—The last continent***

Probably the most critical decision to make when engaging in measuring consumers is to ask yourself: "What do we want to learn from this measurement?" Are we collecting data to observe and find unknown phenomena? Do we want to induce yet unknown structures in known phenomena? Do we want to test deductions about how these can be influenced? Or evaluate the relevance of such predictions in the real world? All of these questions can be important, depending on the research aim. The focus within this "observation-induction-deduction-testing-evaluation" cycle (Fig. 18.4) influences the way we should measure. For observations and induction, as well as evaluation of real-world relevant effects, the method should be exploratory to allow findings of new and unexpected determinants, structures, and phenomena. For deduction testing, internal validity becomes more critical, which implies the tightest possible experimental control, and the method should be able to focus on hypothesized effects ignoring context effects, while for evaluating the outcome, real-world relevance, including external or ecological validity and reflection on the results in the real world context, is essential.

Different stages in this cycle tend to be more relevantly studied with one of the two prominent families of methods: qualitative and quantitative methods. If a phenomenon is occurring in the world and is mostly unknown qualitative techniques such as exploratory observations, interviews and collection of data without a predefined theoretical approach can be helpful to bring in new and unexpected ideas. This often relies on observing and describing unexpected occurrences rather than quantifying their frequency or effect size. Such new ideas and observations can, once somewhat formalized, lead to a collection of more structured quantifiable data from which general rules or new theories can be induced. This can then lead to testable predictions for specific situations deduced from these rules. The results of such tests can then be evaluated and reflected upon in relation to real-world relevance and the starting point of new observations, thus completing the empirical cycle (Fig. 18.4, de Groot, 1969). We argue that completion of observed cycles is an excellent way to ensure the research has both real-life relevances because of observation, induction, and evaluation elements, but is also generalizable to other cases based on deduction and testing.

Incomplete cycles are, however, ubiquitous. The practice in postmodern science is that every situation is unique, and hence theoretical predictions should be avoided (Ravetz, 1999). This results in a lock-in in the top half of the cycle and a stagnation of the number of generally useful ideas that are generated. The fixation in consumer psychology on

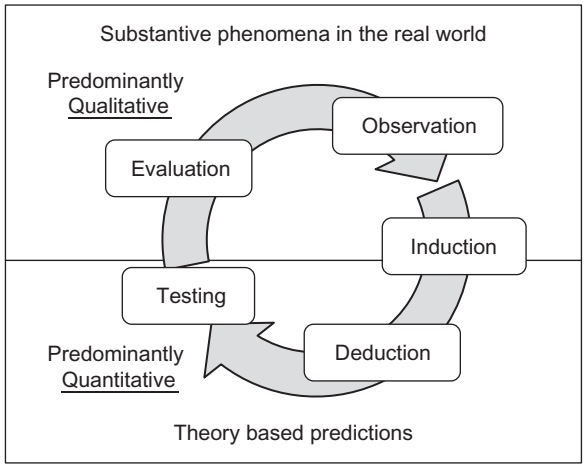

FIG. 18.4 The empirical cycle (de Groot, 1969) in the context of relevant questions in consumer research (Lynch Jr et al., 2012) and types of data collection. *Created by Fischer and Reinders for this publication by combining these sources.*

testing ever more refined theories based on previous theories leads to a detachment with what matters in the real world (Lynch et al., 2012; Pham, 2013). This results in a lock-in in the lower half of the cycle and diminishes the relevance of consumer science to practitioners. Completing the cycle can overcome these lock-ins and is, in our view, an essential yet lastingly underappreciated approach that the field of consumer science should strive for. To do so, the value and use of both qualitative and quantitative methods should be understood.

In the next section, we will introduce some general consumer data deliberations and we discuss deliberation when designing and interpreting studies using a few specific methods. The section will close with a reflection on improvements in consumer science to counter questionable practices.

18.4.1 Data collection methods

The first class of data collection methods in consumer research is "*Qualitative methods*." Qualitative methods are often used for exploratory or interpretative purposes that require a method capable of catching unexpected information from substantive real-world issues. These methods are suitable to identify which essential issues exist and gain an understanding of the underlying reasons, opinions, and motivations of consumers. Qualitative methods are supportive of the development of research ideas or hypotheses that tap into important, substantive real-world issues. Their aim is to bring as many new ideas to the table as possible. These methods tend to be terminated when saturation is achieved, i.e., when novel insights are no longer found. Consumer researchers mainly apply field observations, interviews, focus groups, and laddering interviews as qualitative methods.

Quantitative methods, the second main class, are used to obtain (numerical) data. If sufficiently large data sets are collected in a sample that is representative of the population on relevant variables, quantitative data can be used to induce an overall population profile. The most well-known surveys of this type are probably election polls next to other questionnaires. In the context of food research, surveys are used to quantify attitudes, opinions, behaviors, and other defined variables.[2] Increasingly, individualized sales, geolocation data, and other data from consumers become available, and the quantitative analysis of such behavioral data is also a quantitative approach.

Another application of quantitative methods is in the systematic testing of deduced hypotheses in experimental settings. In the context of food innovations, this can be used to compare the effectiveness of different communication types on consumer attitudes. Experiments typically collect data through questionnaires but also include behavioral data such as choices, time spent in making a choice, eye gaze when reading information or physio-psychological data such as heart rate variability, or even neuroimaging.

Besides "pure" qualitative and quantitative methods, there is also a group of mixed methods such as Q-sort (e.g., Cuppen et al., 2010), Delphi (e.g., Frewer et al., 2011), or repertory grid (e.g., Gupta et al., 2015). These methods can provide a bridge between identifying issues of importance and quantifying consumer opinions and are typically used at the induction phase in the empirical cycle.

The use of multiple methods can be relevant to triangulate toward real-world effects. If one method is not certain enough or leaves open questions, a second method may provide the relevant answers (see, e.g., van Dijk et al., 2017). The more the evidence from different approaches that point in the same direction or complement omissions, the more certain we can be that the identified findings are indicative of real-world consumer behavior. If qualitative, quantitative questionnaires and data from previous research point in the same direction, a more confident conclusion can be drawn.

Merging data to form metadata or other systematic ways to aggregate data across multiple studies can also be required to systematically investigate data from multiple sources in order to arrive at comprehensive conclusions relevant to the field in general (Moskowitz et al., 2005; Moskowitz and Hartmann, 2008). Efforts at creating systematic reviews and meta-analysis on genetic modification publication has adopted this approach (Frewer et al., 2013b; Reinders et al., 2013), although the availability, comparability of data, and the large differences in quality of published literature make many of the conclusions tentative. Thorough deliberation on which measures to use and how to define them will be required to consolidate the field.

In the current digital era, huge amounts of (digital) data are collected and made available. All this data, also referred to as Big Data, cannot be processed or analyzed by using traditional research methods due to its volume and complexity. Therefore machine learning models are increasingly used to process and analyze big amounts of unstructured data

[2] Within consumer science any data that is numeric and allows for mathematical and statistical analyses is considered quantitative. However, some scientific disciplines consider any indirectly measured opinion data to be qualitative, including survey data, consumer opinions measured on a rating scale, etc.

from different data sources. This data can be fed into "learning algorithms," based on which self-regulating models are created, where all new information validates or updates the model (Lillford and Hermansson, 2020). Although still in its infancy, also in relation to novel food acceptance, the first steps are made in using these techniques. For example, Álvarez-Pato et al. (2020) used machine learning regression techniques (i.e., random forest models) to predict consumers' acceptance when trying new food products.

18.4.2 Consumer data considerations

18.4.2.1 Sampling considerations

Collecting data from a relevant sample is critical to good consumer research. What a relevant sample is does depend on the method and research question. A first question, sometimes overlooked, should always be what the study population is. It makes little sense to ask 4-year-old children their preference for a new kitchen oven, as they will (for some years at least) not be the ones using or buying it. The next question is then how to select a sample from the study population (Fig. 18.5).

Qualitative methods often do not depend (nor should they) on a numerically representative sample of the study population. In exploratory research, it is often important to identify as many diverse opinions as needed. Hence a purposive sample from across the research population, where majorities are underrepresented and diverse minorities are overrepresented, is likely to give such broader insights. As a consequence, conclusions about overall opinions, preferences, effects of the intervention, situations, and consumer segments generally cannot be drawn based on these methods. Such an overall conclusion was never the aim of the study, though; these studies tend to be about finding all the important opinions. The sample size of qualitative studies is hence often determined based on the criterion of saturation, which means that data collection is terminated once a prespecified number of observations does not yield any novel insights of substance.

To survey an entire study population and quantify overall opinions, representativeness is essential. How to establish representativeness is less trivial than is often assumed. The researcher has to establish what characteristic representativeness is required. For a producer of weight-loss products, representativeness on body mass index may be critical to assess market potential, while for a producer of insect snacks, representativeness on disgust propensity may be more important. The only truly representative sample, regardless of purpose, requires that all consumer

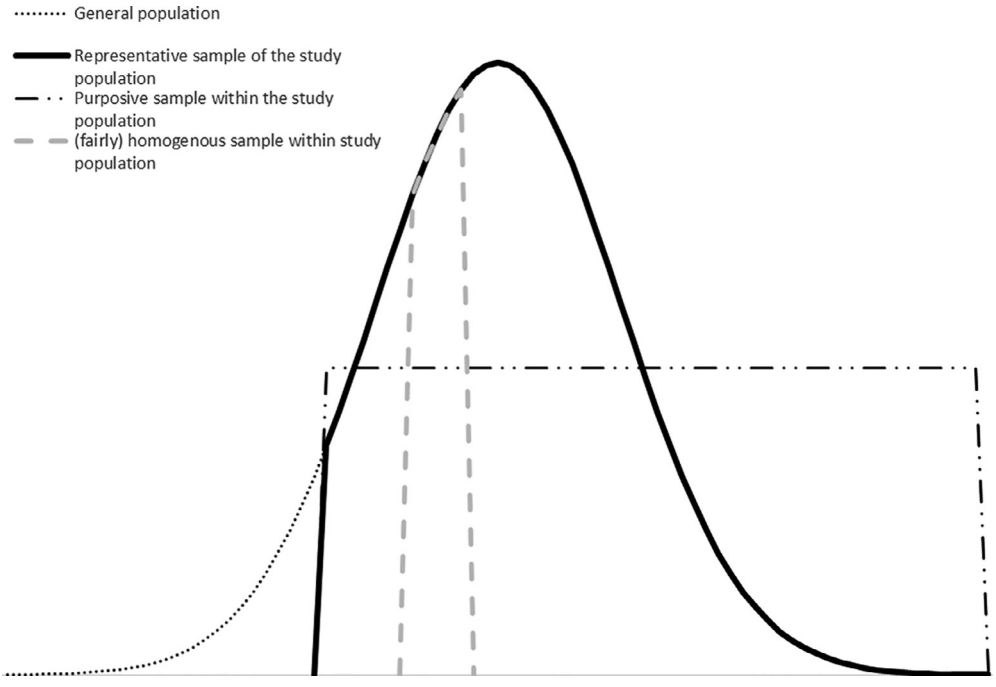

FIG. 18.5 Examples of sampling strategies. Study population is the upper part of the density plot for a normally distributed variable in a fictitious general population. Representative sampling follows the proportion of the general population. In this case, purposive sampling aims for equal representation across all values of the variable (oversampling the upper extreme). A homogenous sample only allows limited variation in the variable (Fischer and Reinders's original work created for this publication).

characteristics and all possible combinations thereof are fully balanced. For example, age and education level effects may interact, which requires balancing not only average education level and age across the sample but also age-education level combinations. We dare to claim that by aiming at a complete representative sample, including less important characteristics and combinations, the only truly representative sample is the entire population. This infeasible situation can be avoided if researchers consciously scrutinize the properties for which a sample should be representative based on their research question.

For experiments, it is less important that the sample is representative of the population. In fact, for experiments, a homogenous sample of similar people can be a benefit as it suppresses uncontrolled variance, thus making the tests more sensitive for experimental effects (improving the signal-to-noise ratio). Nonrepresentative samples are of no major concern as long as differences between the sample and the population are not related to moderating effects, and researchers only make claims about the underlying process and refrain from claiming that parameter estimates and effect sizes[3] can be generalized to the larger population. It is, however, essential that all experimental groups have comparable profiles. This can be ensured by randomization or more advanced techniques such as block randomization or matching.

18.4.2.2 Considerations about measures

Consumer data is tricky data. Ideal consumer data would be stable and clearly anchored. One of the main problems of consumer science is that by measuring consumer opinions and recording behavior according to these opinions, we are likely to change those opinions and behaviors. This can be understood by considering the attitudinal ambivalence and cognitive dissonance literature. Consumers may be perfectly happy with holding contradictory beliefs as long as they do not have to commit themselves. As soon as they have to commit themselves either by making a choice or stating an opinion, they tend to feel discomfort and experience ambivalence (Van Harreveld et al., 2015). This discomfort may then lead consumers to reconsider their beliefs, opinion, and behaviors. Simply asking people their opinion about a topic may trigger this. As a consequence, (1) the answers we require in a survey, where consumers are asked to state an opinion may cause experienced ambivalence, which may lead to consistent answering patterns that do not fully capture consumer beliefs before the question was asked (2) whatever we ask first may influence all subsequent answers to be consistent with those previously committed to statements (3) words and phrases both in the question as in the answer options may "anchor" the response. The choice of how we ask questions and which questions to ask first is thus a nontrivial decision in any consumer study. The anchoring bias means that we cannot interpret opinion values on their own merit. Concluding a significant deviation from the "neutral" option on a Likert scale is irrelevant. We can only interpret such scales as relative, and conclusions should be drawn by comparing similarly recorded opinions on such statements. The effect that previous answers have on subsequent outcomes means that the researchers in both qualitative and quantitative methods have to critically assess which element of the consumer response process needs to be central and tailor the method to pick that element up as cleanly as possible. In doing so, they may have to sacrifice reliability or even the validity of less central responses. For example, if the key question is how information influences consumer choice, where the decision process itself is secondary, assessing the change in choice first is probably a good idea. Subsequent questions on beliefs and attitudes may then, however, be influenced by the already committed choice. If, on the other hand, the key question is how information influences the perception, evaluation, and decision about a product, it is a good idea to start with asking people to report the perceptions first, accepting that expressing these perceptions may influence evaluations, decisions, and choices.

18.4.3 Measurement tools relevant to recording consumer acceptance of novel foods

18.4.3.1 Self-report questionnaires

Questionnaires are relatively easy, quick, and inexpensive to apply and can often be filled out by participants at their leisure. The easy access to online questionnaire tools such as Google Forms and Survey Monkey makes it easy to collect data in a quick and dirty way, without ensuring measurements are done with a reliable and valid instrument. Not surprisingly, from all quantitative data collection methods, questionnaires are by far the most often used by a huge

[3] In particular, effect sizes should not be generalized (just like in vitro effects cannot be generalized to in vivo effects, let alone the real world). Effect sizes (like statistical significance tests) are estimated based on signal-to-noise ratio. By taking a more homogenous sample, variance (noise) in the experiment is artificially reduced in comparison to that in the population, which will make it more easy to identify if there is any effect that may translate to real-world relevance, but effect sizes will be artificially large as noise in real-world settings is larger than in the controlled setting of the experiment.

number of consumer researchers to collect consumer information on acceptance of novel foods (Reinders et al., 2013). Quickly putting out a small-scale questionnaire seems an efficient way to answer research questions. Yet, in spite of its appeal as a quick and cheap instrument, the development of a good questionnaire is a difficult yet frequently underestimated task. For the domain of consumer science as a whole, the abundance of consumer questionnaires may even be more of a barrier against progress than a benefit. Unless questionnaires start using the same validated groups of questions, individual questionnaires have limited relevance to developing a more generally applicable resource for predicting consumer response.

Questionnaires are a relevant method when a clear a priori theoretical idea of relevant attributes and contexts is known (Barrios and Costell, 2004; Iop et al., 2006). These theoretical approaches will then determine what question to include, that is, how the theoretical constructs are operationalized in the survey. Different theoretical approaches will almost unavoidably lead to different measures. For example, while a subjective utility assessment (e.g., Kahneman and Tversky, 1979) has similarities with attitude judgments (e.g., Fishbein and Ajzen, 1975), the differences result in substantial differences in how the two constructs are generally measured. Utility assessment tends to ignore emotional reaction to the product and tends to express the outcome in monetary terms. This can be measured by asking participants how many Euros, Dollars, or whatever local currency applies they are willing to pay. The predictive validity of these is often rather poor as participants do not have to sacrifice their own money to obtain the product. To overcome this problem, much effort in economic psychology is paid to creating methods that do include such sacrifice, for example, by auctioning the product among participants. Attitude measures, in contrast, tend to focus more on the internal structure of the opinion than on whether it fully captures the actual sacrifice people are willing to make. Many measures include questions on cognition (fairly close to expected utility) but also ask for feelings and reflections on past behavior (e.g., Ajzen, 2001; Eagly and Chaiken, 1993). Attitude is generally measured with more than one question to capture all of that.

But even if the construct is defined the same way, measures for that same construct are often wildly different (Reinders et al., 2013). Constructs like risk perception, benefit perception, trust, knowledge, attitude, and willingness to pay are frequently used, yet different researchers define these constructs in different ways (Hendrick et al., 2013; Reinders et al., 2013). This inconsistent use of measures has long dismayed some consumer scientists (Churchill, 1979) but is sometimes even encouraged by leading practitioners (see, e.g., Ajzen, 1991). More consistent use of measurement scales for these constructs would provide a much better baseline for future comparisons and limit the problems that meta-analyses encounter today (see, e.g., Frewer et al., 2013b). A complicating factor is that it may be essential to validate translations into different languages to separate linguistic from cultural differences as much as possible (Steenkamp and Baumgartner, 1998). Developing a scale in this way is labor-intensive.

Nevertheless, consumer scales can be developed to be a rigorously validated instrument, an approach advocated by early developers of self-report measures such as Thurstone and Likert (Churchill, 1991).

To build toward a generally applicable body of research about consumer response to innovations, it is important only to use measures (1) of the highest possible quality, i.e., psychometrically validated, and (2) whenever possible use the same scales, to allow comparison of effects across different product samples and situations.

This approach will not solve a more intrinsic issue with self-reported data obtained by questionnaires. Questionnaire data is subject to all kinds of biases from the side of the respondents (i.e., social desirability, response bias, sampling bias). Leading questions may evoke specific answers or, somewhat less disturbing, an anchoring effect where the questions suggest a baseline to the answer. Self-reported measures are sensitive to socially desirable or self-enhancing responses, especially for sensitive topics like new technologies or innovations, as participants consciously reflect on their answers. An effort to develop approaches to circumvent these limitations may be found in the types of methods next.

18.4.3.2 Implicit attitude measures

In social psychology, the past twenty-five years have been devoted to developing instruments for measuring consumer opinions indirectly. This approach aims to overcome the fact that many simple decisions are made unconsciously while opinions are conscious. In addition, undesirable responses like racial or gender stereotyping may be canceled out in explicit attitude statements while they may inform these unconscious decisions. Conceptually, associative evaluations are defined as those associations that come to mind unintentionally, that are difficult to control once they are activated, and that may not necessarily be endorsed at a conscious level (Galdi et al., 2008). Many empirical measures for implicit associations are based on participants' performance on computer-based, speeded categorization tasks (Gawronski and Bodenhausen, 2006), for example, by computing the time that a respondent needs to pair two concepts (Karpinski and Steinman, 2006). Examples of implicit measurement instruments are the Implicit Association Test, which asks participants to assign stimuli to one of two categories (IAT Greenwald et al., 2003), and the Affective

Priming Task, which asks people to give a positive or negative response to a stimulus (Fazio, 2001). The Affect Misattribution Procedure is one of the few untimed tasks. It asks participants to rate a seemingly unrelated object after seeing the stimulus, assuming that the associations of the stimulus carry over to the unrelated object (Payne et al., 2005). For a more complete overview, see Goodall (2011). While it is not clear to what extent innovations are controversial per se, it seems that in the case of innovative food products, implicit measures have some limited added value but this value is often preliminary or nonconsistent (Bekker et al., 2017, 2021; de Beukelaar et al., 2019; Spence and Townsend, 2006; Tenbült et al., 2008).

Other ways of measuring implicit or intuitive reactions are of psychophysiological nature, i.e., measures that use physiological responses to a situation to measure psychological constructs such as preference. These measurement instruments include, e.g., Eye tracking, which can be used to track attention focus and attitude formation for new technologies (van Giesen et al., 2016), Heart Rate Variability (HRV) and Galvanic Skin Response (GSR), which can measure arousal, although it is less clear to what extent arousal can be unambivalently interpreted in terms of consumer opinion (Wang and Minor, 2008). Brain-based measures include Electro-Encephalography (EEG), measuring brain activity, and functional Magnetic Resonance Imaging (fMRI), which can measure brain activation in specific locations. fMRA interpretation is gradually improving and is focusing on what brain regions are related to reward feelings in the brains. Identifying active brain centers for specific thoughts about innovations and how this will work out in a real-life context has been and remains a challenge.

Consumer opinions about food innovations are often hardly formed attitudes that are not necessarily controversial. What all approaches to implicit measures have in common is that they provide the most consistent results if people have strong opinions. In addition, for dealing with consumer responses for noncontroversial topics, explicit measures such as surveys often align almost perfectly with implicit measures. While it may be "sexy" (Lebel and Paunonen, 2011) to use advanced measures, in fact, it is also considerably more labor-intensive and expensive. Given the problematic reliability of these methods, and especially in cases where only little added value of advanced methods is expected, it may often be better to opt for traditional methods.

18.4.3.3 Overt behavior methods

Given the limitations of opinion data, either self-reported or implicit, measuring overt behavior can be a relevant alternative in some cases. Various methods are increasingly applied.

Transaction data from supermarkets or other food outlets can be used to measure consumer purchase data. Numerous commercial marketing companies continuously collect and aggregate this kind of data through scanner technologies. A major advantage is that this data could reveal food and drink purchases on large samples and at the highest level of product detail and combine them with specific product information. However, a disadvantage is that this data cannot directly be linked to consumer behavior on an individual level, as individual purchases do not necessarily inform about an individual's consumption behavior (for instance, groceries are normally bought at the household level but can potentially also be bought for someone else). In addition, the unit of analysis is a single store visit, unless longitudinal data for the same shopper can be linked through, e.g., loyalty programs.

In addition, smartphones and wearables allow for tracking consumers through GPS in combination with surveying, through apps, for example. This not only allows for combining food intake with location data but also for obtaining insight into other spatial effects in consumer behavior. Wearable sensor technology, coupled with advanced algorithms, is increasingly showing promise in its ability to capture behaviors that provide useful information for consumers' response to novel food products. An important issue that needs to be addressed in conducting this research is protection of consumers' privacy.

18.4.4 The replication crisis and why it is good

The year 2011 can be considered to be one of the worst and best years ever for social psychology, a field closely related to consumer science. In the spring of 2011, the leading Journal of Personality and Social Psychology published a paper by Daryl Bem (2011) claiming that his participants responded to computer stimuli prior to their presentation; that is, Bem claimed evidence of precognition. In the summer of the same year, the well-known Dutch psychologist Diederik Stapel was caught having fabricated data during most of his career. Subsequently, 58 of his papers were retracted (including one in Science). This obviously was a shock to the community. It urged the psychology community to start cleaning out its mess.

One of the actions undertaken was an effort to replicate 100 recent experiments in leading psychology journals. Then, as a shock to many, the outcome was less than half replicated (A. A. Aarts et al., 2015). The replication crisis

in social science had begun. To be fair to psychology, when writing the 100 replications paper, it turned out that no other scientific domain had ever assessed the proportion of failed replications before, and no unambiguous measures for replication success existed. The best estimates of proportions of replicable results by experts in medicine and cell biology in their own fields were, in fact, similarly worrying as those observed for the psychology experiments (A. A. Aarts et al., 2015).

The Stapel case, one of outright fraud, was considered as a case where everyone agreed it was malpractice. But the Dutch Royal Academy team investigating the Stapel case identified a gray area of cutting corners being common in psychological research. This gray or ugly area was deemed more problematic than outright fraud (Levelt et al., 2012). This gray or ugly area consists of questionable practices, practices we never learned at university, but openly, sometimes even proudly, discuss with peers. The editor of the Journal of Personality and Social Psychology asked reviewers to critically but fairly assess against common practices in the field. All practices applied by Bem had been long common in the field and hence not ground for rejection. The editor also invited a methodological paper to accompany Bem's, 2011 paper. The authors of that paper argued that Bem's findings could easily be caused by methodological tricks and cutting corners rather than a true parapsychological effect (Wagenmakers et al., 2011). Since that time, a debate has been ongoing about such questionable yet common research practices. An often framed term in this context is that of "researcher degrees of freedom," indicating additional, post data collection actions a researcher can take to improve the chances of finding evidence for their ideas.

Suggestive presentation of true data can already be seen as dodgy (the short book How to lie with statistics by Darrel Huff, 1954 remains highly recommended). Questionable research practices can, however, change the outcomes at their core. We name some of these practices where researchers try to "improve" significances and present exploratory induction as testing of deductions. Note that cleaning up of data is often needed and perfectly fine as long as we decide what to do before we do it. Post hoc data cleaning and selection can lead to false positives easily by:

- removing outliers, i.e., those participants that, according to the researcher, do not belong in an experiment group and
- adding control variables from a large set that was collected and added merely because, in retrospect, they "clean up" the statistics.

Researchers can similarly increase the possibility of finding (false positive) results by capitalizing on the fact that with the common critical $p = .05$, we accept a false positive for 1 in 20 tests. By running more tests and only reporting the ones that gave significant results, the probability of a false positive obviously increases (compare with rolling a die on a board game and only count the number of sixes rolled with the die, subsequently concluding that this particular die only rolls sixes). Typical, and in the past largely accepted, practices that rely on this include:

- Collecting multiple outcome variables and only reporting those that show effects.
- Revising and rerunning experiments until you find an effect.
- Selectively rewriting observed relations as predicted outcomes from a theoretical rationale: Hypothesizing After Results are Known (Harking).
- Adding participants until effects are shown. Since information about partial results is used in the procedure, it does not only increase power (as many assume) but also increases the chance of false positives.[4]

Not all blame should be assigned to individual researchers, however. Many questionable actions are encouraged by a journal's reluctance to accept exploratory papers and nonsignificant results; the emphasis in top journals and university tenure track systems lies on finding more creative and counterintuitive effects. Hence we should also consider the responsibility of academia as a whole for these practices. While none of these insights are new, it took the replication crisis for psychology to start working on these in earnest.

[4] This seems counterintuitive as an increasing sample size generally makes estimates more precise, i.e., increase power. But that is not the whole story. Consider a series of 20 experiments in a situation where nothing is going on (h0 is true). We would expect that the experiment with the (randomly generated) most extreme values would give about 1 false positive and 19 (true) negatives; this is after all what a critical p of 0.05 implies. Now consider what happens if we double the observations of these remaining 19 nonsignificant experiments (true negatives). Some of the randomly generated extreme outcomes in this second run may now cause some of these 19 experiments to become a false positive (albeit less than 5% given the less than extreme values in run 1 that are combined with the additional results). If we would have collected the large data set from the start, this would be compensated for by some false positive experiments that, having extreme values during the first half of data collection, are being corrected by the additional observations. However, by looking at the data halfway through and stopping data collection at the reached significance, the false positives from run 1 can never be corrected and become a true negative. The probability of a false positive in the combined runs 1 and 2 is thus more than 5%.

An important step toward improvement is the increasing emphasis on preregistration of studies, where, prior to data collection, the hypotheses, measures, numbers of required participants, data cleaning, and analysis procedures are stored. This has shifted attention to a priori consideration of the statistical power of studies, effect sizes, and the use of alternative statistical procedures (reviving earlier calls to arms from Cohen, 1992b). The emphasis of journals and funders to store underlying data in a findable, accessible, interoperable, and reusable (FAIR) way in depositories is also helping toward more open science where questionable practices are hard to conduct. Psychology is catching up and, in some areas, becoming a front runner in such best practices. While the replication crisis has caused considerable damage to the public image of psychology, and the field remains far from perfect, the replication crisis may still be one of the better things that happened.

18.5 Conclusion and future outlook

Consumer science offers a wealth of theoretical and empirical approaches that can be of use in the development of food innovations.

Current consumer science movements are aligning toward approaches where less of the consumer behavior is considered to be based on conscious and deliberate choice. Instead, implicit, often unconscious, gut feelings and the influence of the environment through choice architecture are shown to influence consumer behavior. Cocreation aims to tap into the same unconscious knowledge base by involving consumers in the design phase. In applied work, more traditional methods such as questionnaires still dominate. When correctly, consistently, and relevantly applied, these methods can still contribute immensely to our understanding of consumer response to food innovations.

New technological developments are enriching the field's methodology, moving it beyond its traditional focus on self-report measures. New information technologies such as wearables, the internet of things, and smartphone data begin to enrich the food consumer science field with new types of "big data" (Timmins et al., 2018). Additionally, reconstructed reality (e.g., virtual reality, augmented reality, and immersion rooms) can be used to create an environment to study consumer behavior.

Harvesting data from the web provides researchers the possibility to obtain insight into spontaneous information from a large number of consumers. Tools for obtaining and validating this information (e.g., text mining, web scraping) offer future potential. Where most of the 20th century food technology depended on creating large volumes of products with homogeneous (high) quality at low cost, interactive internet services increasingly allow consumers to order tailored products. Personal selection of sweets is already possible (e.g., specified M&M colors), and it is possible to upload photos for birthday cakes, which may evolve into home-specified 3D shapes. Tailoring personalized nutritional profiles based on someone's health status or even genetic profile is being developed.

Given the complexity of consumer's psychological decision-making, embedded in their social and societal context for each study, it is important to raise specific questions and carefully select theory, methods, and measurements to use before data is collected. This chapter presented several alternative theories, methods, and measurements, and, as such, may not have provided clear-cut answers. This has never been our intention. In this chapter, we aimed to share our fascination with the many deliberations needed and alternatives that can be considered to ensure high-quality consumer research relevant to innovations in food.

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