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Consumer self-tracking behavior:
An investigation of the drivers and outcomes of self-tracking

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Abstract

Despite the increasing popularity of self-tracking technologies in the market (e.g., activity tracking devices and apps), consumer adoption of these technologies continues to be a challenge, and there exists concerns about the benefits of using such technologies. The current dissertation investigates the likely drivers, as well as the outcomes, of consumer self-tracking behavior in order to provide a comprehensive understanding of the phenomenon. Therefore, the current dissertation examines two main research questions: (1) What factors influence consumer adoption or use of self-tracking technologies, and how? (2) How do self-tracking technologies influence various consumer outcomes (e.g., motivation, experience, and well-being), and what are the roles of individual (e.g., types of consumers) and contextual (e.g., types of activities) factors?

The current dissertation is comprised of three separate papers. Paper 1 undertakes a systematic review of the extant literature on self-tracking behavior, specifically in the context of fitness tracking, to explore the current state of knowledge on the drivers and outcomes of self-tracking behavior. Based on the review, paper 1 identifies 18 drivers of fitness-tracking technology adoption (e.g., age, technology affinity, data quality, and perceived device value etc.) and reveals four main outcomes of fitness tracking (e.g., task motivation, task experience, physical activity level, and well-being/health). Paper 2 examines a situational factor (i.e., incidental curiosity) that can facilitate consumer self-tracking behavior and explains the causal mechanism. Three experiments demonstrate that incidentally induced curiosity enhances consumers' perceived value of curiosity-relevant unknown information (e.g., answer to a puzzle). This positive perception in turn spills over to other curiosity-irrelevant unknown information—increases perceived value of curiosity-irrelevant unknown information (e.g., unknown self-related information). As a result, incidental curiosity increases consumers' intention to use self-tracking technologies. Paper 3 explores the effect of self-tracking on consumer experience (i.e., enjoyment, subjective vitality) by considering the role of both individual and contextual factors. Three experiments demonstrate that, for effortful tasks, self-

tracking has contrasting effects on the task experience of different consumer segments: i.e., a positive effect on the females versus a negative effect on the males. This is due to females' (vs. males') tendency to underestimate (vs. overestimate) themselves. As self-tracking feedback can help females realize that they are more capable than they previously thought, self-tracking increases females' (vs. males') perceived competence, which in turn increases females' (vs. males') task experience. The findings of the current dissertation provide important insights for both consumer researchers and marketing practitioners.

Keywords

Drivers, experiments, literature review, outcomes, self-tracking

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Chapter 1

1. Introduction

1.1 The emergence of self-tracking phenomenon

Data, algorithms, and numbers play a powerful role in today's society; indeed, consumers are living in an era where their lives are increasingly shaped by numbers (Ajana, 2018). Over the years, the market has witnessed the emergence of commercial technologies (e.g., smart devices, apps), which allow consumers to monitor and track various personal information (e.g., physical activity, sleep pattern, and calorie intake) in numbers (Shin, Cheon, & Jarrahi, 2015). The proliferation of these tracking technologies and devices (e.g., Fitbit, Jawbone, and Nike+ Fuelband) has led to the rise of self-tracking practices, also known as self-quantification (Ajana, 2018). As a result, consumers now have access to more information about their lives than ever before (Etkin, 2016), and many consumers have become attracted to the idea of using self-tracking technologies to learn about themselves (Jarrahi, Gafinowitz, & Shin, 2018).

According to Canhoto and Arp (2017), self-tracking technologies have achieved an increasing degree of public awareness and integration into consumers' lives. For instance, approximately 90 million activity-tracking devices were sold in 2014 (Jarrahi et al., 2018), over 100 million were sold in 2016 (Attig & Franke, 2018), and demand is expected to remain strong (Jarrahi et al., 2018). Consequently, self-tracking technologies are becoming increasingly commercially available (Lazar, Koehler, Tanenbaum, & Nguyen, 2015), and they are expected to become an important part of consumers' lives (Coorevits & Coenen, 2016).

1.2 The challenges with consumer adoption of self-tracking technologies

Although the popularity of self-tracking technologies is expected to increase, the market of these technologies is not free of challenges (Clawson, Pater, Miller, Mynatt, &

Mamykina, 2015; Shih, Han, Poole, Rosson, & Carroll, 2015), and one of the current issues is the relatively low adoption rate of self-tracking technologies (Canhoto & Arp, 2017; Chang, Lu, Yang, & Luarn, 2016). While some consumers have a positive attitude toward self-tracking technologies, others are either reluctant to adopt these technologies or use them in the long run (Coorevits & Coenen, 2016). For example, approximately 30% of users abandon their wearable activity-tracking devices within the first 6-12 months, while more than half of consumers stop using their devices altogether (Canhoto & Arp, 2017; Jarrahi et al., 2018; Rupp, Michaelis, McConnell, & Smither, 2018). It appears that avoiding or discontinuing the use of self-tracking technologies is common among consumers (Epstein et al., 2016), and therefore the adoption of self-tracking technologies is both limited and short-lived (Chang et al., 2016).

This relatively low adoption rate (or high attrition rate) indicates that self-tracking technologies are not currently meeting the needs or expectations of consumers, which poses a threat to the long-term growth and development of the self-tracking industry. Therefore, an in-depth investigation into the interaction between self-tracking technologies and consumers is needed to identify the drivers (or barriers), as well as the theoretical foundations, of self-tracking technology adoption. Understanding the drivers of consumer adoption of self-tracking technologies is of great importance for marketers of self-tracking products, as early adopters can increase initial sales and provide positive word-of-mouth for other potential consumers (Alka, David, Steven, & Donald Jr, 2000). The insights on the drivers of self-tracking technology adoption can also help marketers translate valuable marketing dollars into higher consumer adoption (Alka et al., 2000). For example, marketers can implement more efficient segmentation strategies or advertising campaigns if they can identify which type of consumers are more likely to use self-tracking technologies.

1.3 The concerns over the effectiveness of self-tracking technologies

The challenge, however, does not end here. Another important concern that arises together with consumer adoption is the outcomes of self-tracking behavior; namely, how self-tracking technologies influence consumers' everyday lives (e.g., activities), and to what extent and in which manner do these technologies mediate consumers' everyday experiences (e.g., enjoyment). Often, self-tracking technologies are marketed as efficient tools for promoting positive consumer outcomes (e.g., fostered self-knowledge, enhanced motivation, increased physical activity, or improved health; Jarrahi et al., 2018) by providing various personal information (e.g., steps walked, distance ran, and calories burned; Preusse, Mitzner, Fausset, & Rogers, 2017). However, the relatively low adoption rate of self-tracking technologies may indicate their potential lack of efficiency in delivering such benefits. In fact, there exists growing skepticism regarding the positive effect of self-tracking on consumers (Clawson et al., 2015; Etkin, 2016). Thus, it is important for the producers of self-tracking technologies to understand the impact of self-tracking on consumer outcomes to better design these technologies.

To date, a comprehensive understanding of the effect of self-tracking technologies on various consumer outcomes (e.g., motivation, experience, or well-being) is lacking. Therefore, a thorough investigation of the outcomes of self-tracking behavior is needed to add to our knowledge of such behavior (e.g., when and to whom do self-tracking technologies generate positive outcomes). In addition, as consumer motivation and experience are positively associated with consumer engagement (Banyte & Gadeikiene, 2015), insights regarding the effect of self-tracking technologies on consumer outcomes could be valuable for firms who are interested in facilitating consumer engagement (e.g., gyms, sports centers). Marketers of self-tracking products may also use such knowledge to effectively communicate the benefits of their products and to promote their products to the proper consumer segments. By inducing positive outcomes (e.g., enjoyment) of self-tracking technologies, marketers can facilitate the use of self-tracking technologies among consumers, and thus connect to more consumers on a daily basis

(e.g., through tracking devices or apps), which would allow marketers to collect valuable consumer data that can be utilized to improve the performance of their marketing campaigns.

1.4 The agenda of the current dissertation

Given this background, the general objective of the current dissertation is to investigate the likely drivers and outcomes of consumer self-tracking behavior. The current dissertation thus pursues two main research questions: (1) What factors influence consumer adoption or use of self-tracking technologies, and how (e.g., causal mechanism)? (2) How do self-tracking technologies influence consumer outcomes (e.g., motivation, experience, and well-being), and what are the roles of individual (e.g., types of consumers) and contextual (e.g., types of activities) factors?

To answer these questions, the current dissertation first conducts a systematic review of the extant literature on self-tracking to explore the current state of knowledge on the drivers and outcomes of self-tracking behavior and to identify potential gaps. To provide cohesive insights, the literature review (paper 1) focuses specifically on the context of fitness tracking to investigate both the drivers and the outcomes of self-tracking behavior. Fitness was chosen as the context for this investigation, because it is a field where self-tracking technologies have been widely used and applied in real life (Jarrahi et al., 2018). Therefore, such a comprehensive review of the existing literature on fitness tracking can provide useful insights for practice. Furthermore, the current dissertation conducts two more empirical research based on the gaps identified in the literature review (paper 1). Specifically, the first empirical paper identifies a situational factor (i.e., incidental curiosity) that can facilitate consumers' intention to use self-tracking technologies, as well as examines the causal mechanism of the identified effect (paper 2). The second empirical paper provides empirical evidence on the effects of self-tracking technologies on consumer experience (i.e., enjoyment, subjective vitality) by considering the role of both individual (i.e., gender) and contextual (i.e., effortful task) factors (paper 3).

The summary of this dissertation is organized as follows: The theoretical perspectives of the current dissertation are discussed in the following chapter. The research methodology is then outlined in the third chapter. In chapter four, the findings of the current dissertation are presented. Then, in the fifth chapter, the theoretical and managerial contributions of the current dissertation are discussed. The last chapter presents the limitations of the current dissertation and suggestions for future research.

Chapter 2

2. Theoretical perspectives

2.1 Self-tracking: a new way of seeking information

Recent technological advancements have led to a new way of seeking information—self-tracking (or self-quantification). Self-tracking refers to the use of modern technologies to automatically track and collect personal information in numbers (Lee, 2013). Self-tracking technologies are smart technologies that are designed to monitor consumers' everyday activities and provide self-related information (or feedback) so that consumers can understand, and possibly modify, their activities and behaviors (Crawford, Lingel, & Karppi, 2015). With an increasing number of self-tracking technologies (e.g., activity trackers, apps) becoming commercially available, consumers are quickly becoming active seekers of information rather than passive receivers. Consumers are now also less limited by external conditions (e.g., location, time) in obtaining information about themselves. For example, by using activity trackers (e.g., Fitbit), consumers no longer need to go to a specific medical facility or professional expert to obtain information about their health (e.g., body mass index) or physical activity levels (e.g., performance). As a result, many consumers have begun routinely tracking their activities and a myriad of behavioral variables (Ajana, 2018).

In response to the widespread application of self-tracking technologies in practice (e.g., medicine, fitness, and business ; Rheingans, Cikit, & Ernst, 2016), an increasing amount of research has begun to explore the drivers and outcomes of self-tracking behavior (e.g., Attig & Franke, 2018; Canhoto & Arp, 2017; Stiglbauer, Weber, & Batinic, 2019). Although previous studies provide important insights, more research is needed to improve our understanding of the self-tracking behavior. For example, previous research has mostly applied the Technology Acceptance Model (TAM) or the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) Model to investigate the drivers of self-tracking behavior (e.g., McMahon et al., 2016; Mercer et al., 2016;

Preusse et al., 2017; Rheingans et al., 2016). Therefore, the constructs from the TAM or UTAUT2 (e.g., perceived ease of use, perceived usefulness, and perceived value) have primary been explored as potential explaining factors, while the underlying factors of these constructs themselves have been largely underexplored. Indeed, little is known about what factors influence consumers' perceptions (e.g., useful, valuable) of self-tracking technologies or how marketers can enhance consumers' perceived usefulness or value of self-tracking technologies to facilitate the use of these technologies. The current dissertation thus argues that incidental curiosity, as a situational factor, can facilitate consumer self-tracking behavior by enhancing consumers' perceived value of unknown information (e.g., unknown self-related information).

Another line of research in the literature has investigated the likely outcomes of self-tracking behavior: namely, the effect of self-tracking on consumer outcomes. While several studies have explored the motivational and behavioral impacts of self-tracking on consumers (e.g., Butryn, Arigo, Raggio, Colasanti, & Forman, 2016; Pettinico & Milne, 2017), the experiential side of self-tracking as a daily practice has received little attention in the literature. In addition, the limited amount of research that has examined the effect of self-tracking on consumer experience (e.g., enjoyment) remains inconclusive. For example, while a number of studies have suggested that self-tracking has a positive effect on consumer enjoyment (e.g., Canhoto & Arp, 2017; Mauriello, Gubbels, & Froehlich, 2014), Etkin (2016) has found that self-tracking has a negative effect on task enjoyment. Due to contradictory findings within the literature, further investigation is required on this topic. Thus, the current dissertation investigates the effect of self-tracking on consumer experience by considering the role of individual and contextual factors to improve our understanding of the effect of self-tracking and provide marketers in the self-tracking industry with useful insights.

2.2 Curiosity and self-tracking: the role of perceived value of unknown information

In general, curiosity is a complex feeling that accompanies the desire to learn what is unknown (Bowler, 2010; Kang et al., 2009), and thus is a powerful motive that influences human behavior (Loewenstein, 1994; Steenkamp & Baumgartner, 1992). According to Wang and Huang (2017), curiosity can be aroused by either a feeling of interest (I-type) or a feeling of deprivation (D-type). These two types of curiosity correspond to very different motives for acquiring unknown information (Litman, 2008). I-type curiosity reflects a desire to acquire knowledge for the purpose of intrinsic interest, such as reading the latest news about your favorite football team (Isikman, MacInnis, Ülkümen, & Cavanaugh, 2016). This type of curiosity is characterized by diverse information acquisition and is related to a relaxed feeling of acquiring curiosity-relevant (or interest-relevant) unknown information (Litman, 2010; Schneider, Von Krogh, & JäGer, 2013).

Conversely, D-type curiosity can be conceptualized as a cognitive deprivation that arises from an information gap (e.g., an incomplete story) between what one currently knows and what one desires to know (Loewenstein, 1994). For example, solving a puzzle can arouse one's curiosity by making an individual identify the information gap—the answer to the puzzle. Therefore, D-type curiosity arises when one identifies or becomes aware of the lack of needed information, i.e., is deprived of the curiosity-relevant unknown information (e.g., answer to a puzzle), and increases with the information gap becoming smaller (Grossnickle, 2016; Isikman et al., 2016). Because an information gap (vs. simple interest) is associated with higher level of wanting curiosity-relevant unknown information (Litman, 2005; Wang & Huang, 2017), D-type (vs. I-type) curiosity is more likely to influence consumers' perceptions (e.g., perceived value) of such unknown information. Thus, the current dissertation focuses on D-type curiosity and, for the sake of simplicity, the term "curiosity" is used to refer to D-type curiosity.

According to past research, deprivation creates a need state (e.g., need for food, need for money), which can influence consumers' perceptions of the need-related stimuli (Briers, Pandelaere, Dewitte, & Warlop, 2006; Seibt, Häfner, & Deutsch, 2007). For

example, food deprivation can increase the incentive value of food (Bulik & Brinded, 1994; Raynor & Epstein, 2003). Curiosity, as a form of cognitive deprivation, can thus also create a need state (e.g., need for information), which can positively influence consumers' perceptions (e.g., perceived value) of the need-related stimuli—curiosity-relevant unknown information. In addition, given that perceptions can spillover among objects that have shared attributes or associations (Du, Bhattacharya, & Sen, 2007; Janakiraman, Sismeiro, & Dutta, 2009; Roehm & Tybout, 2006), the positive perception of curiosity-relevant unknown information can spill over to other information that has the same attribute—unknown (i.e., curiosity-irrelevant unknown information). As a result, curiosity can increase the perceived value of other unknown information, such as the unknown self-related information that self-tracking technologies provide.

As discussed in section 2.1, self-tracking technologies provide consumers with a variety of information (e.g., steps, running distance, heart rate, and calories burned) that can be difficult to know or obtain without the help of these technologies. The information that consumers obtain through self-tracking is often unknown information, which suggests that, when curious, consumers may perceive such unknown information as valuable. This positive perception toward unknown information would increase consumers' responsiveness to the unknown self-related information that self-tracking technologies provide. As a result, incidental curiosity would make self-tracking technologies appear more attractive, and increase consumers' intention to use (e.g., choice, willingness to pay) self-tracking technologies. Therefore, curiosity can be an influential driver of consumer self-tracking behavior. It is subsequently necessary to determine what happens after consumers adopt or start to use self-tracking technologies: namely, how does self-tracking affect consumers' lives (e.g., experience)?

2.3 Self-tracking and task experience: from the perspective of self-determination theory

Self-tracking technologies, by being embedded in a wide range of everyday objects (e.g., smartphone, cutlery, and clothes), have the potential to mediate consumers' everyday

experiences. Therefore, it is equally important to investigate the outcomes of using self-tracking technologies; e.g., how self-tracking influences consumer experience of various tasks. As discussed in section 2.1, self-tracking technologies provide consumers with valuable data (e.g., numerical feedback) regarding their behaviors or activities. For example, fitness trackers (e.g., Fitbit) give consumers real-time feedback on their activity levels (e.g., number of steps, number of kilometers). Since previous research has shown that feedback can influence an individual's experience (e.g., enjoyment) of a given task (Deci, Koestner, & Ryan, 1999; Ryan & Deci, 2017), self-tracking technologies may also serve to mediate consumer experience by providing consumers with self-related information as feedback.

According to the self-determination theory (SDT), people's psychological states (e.g., motivation, enjoyment) are significantly affected by the satisfaction of their basic psychological needs for autonomy (e.g., sense of volition), competence (e.g., feelings of mastery), and relatedness (e.g., feel socially connected) (Deci & Ryan, 2000). Indeed, SDT argues that external events (e.g., feedback) enhance people's task experience (e.g., enjoyment, subjective vitality) to the extent that such events satisfy their need for competence (Ryan & Deci, 2017). Therefore, self-tracking feedback (e.g., self-related information), as an external event, can also positively influence consumer experience, as it can enhance consumers' perceived competence.

It is important to note that the effect of self-tracking on consumers' experience may be individually constructed based on their different perceptions of external feedback. That is, self-tracking can either increase or decrease one's task experience, depending on whether he or she perceives self-tracking feedback as either informational (e.g., emphasizing their competence) or controlling (e.g., a pressure to behave in a particular way) (Attig & Franke, 2018). For example, self-tracking feedback can have different effects on females and males. Previous studies have indicated that females' and males' perceptions of the informational value of feedback differs significantly: females are more likely to perceive external feedback as informational (Henderlong Corpus & Lepper, 2007; Roberts, 1991; Roberts & Nolen-Hoeksema, 1989). In addition, the effect

of self-tracking can also be highly context-dependent. For example, it is well-established that positive feedback can increase an individual's enjoyment or subjective vitality in effortful tasks (vs. effortless tasks) by increasing the subject's perceived competence (Deci et al., 1999; Ryan & Deci, 2008). Thus, self-tracking is more likely to have a positive impact on consumer experience when used for effortful tasks (vs. effortless tasks).

In summary, the use of self-tracking technologies by different individuals, and within different contexts, can result in different outcomes. Therefore, both individual (e.g., types of consumers) and contextual (e.g., types of activities) factors need to be taken into account when investigating the effects of self-tracking technologies on consumer outcomes (e.g., experience). Currently, research regarding the effects of self-tracking technologies on consumer experience is limited (Attig & Franke, 2018). Therefore, more empirical studies are needed to either prove or disprove the assumed positive or negative impacts of self-tracking on consumer experience (Selke, 2016).

Chapter 3

3. Research methodology

3.1 The research approach

Research approach refers to the research methods—the systematic collection of data for the purpose of investigating a particular research question—that are applied during a research project (Ghauri & Grønhaug, 2005). The current dissertation consists of three separate papers based on two different research approaches: a systematic literature review and an experiment. According to Aromataris and Munn (2017), a systematic review of the extant literature is an efficient way to summarize existing knowledge and to uncover relevant evidence to a specific research question. Therefore, in paper 1, a systematic review of the self-tracking literature is conducted to provide a comprehensive analysis of relevant empirical research conducted in the field. On the other hand, an experiment is a quantitative approach designed to discover the causal effects of presumed relationships (Christensen & Waraczynski, 1988). A key feature of this approach is that only one variable—the independent (experimental) variable—changes, while the rest remain constant. Therefore, an advantage of this approach is the researcher's ability to manipulate precisely one (or more) variable (Christensen & Waraczynski, 1988). In paper 2 and paper 3, a series of experiments is conducted by manipulating the key experimental variables (e.g., curiosity, self-tracking) to investigate the causal mechanisms of the proposed effects: for example, the effect of incidental curiosity on intention to use self-tracking technologies, and the effect of self-tracking on task experience.

3.2 The data

The entire data collection process lasted from 2017 to 2019. According to Ghauri and Grønhaug (2005), there are in general two types of data: primary data and secondary data. Primary data refers to original data that is collected by a researcher for a specific

research question, whereas secondary data refers to data that has already been collected by others for a different purpose, and is subsequently reused by a researcher for another research purpose (Hox & Boeije, 2005). Both types of data have their own advantages and disadvantages (e.g., flexibility, cost), and thus researchers collect different types of data based on the purpose of their research. For the current dissertation, both secondary data and primary data were collected to investigate the specific research questions at hand.

Specifically, paper 1 collected secondary data—previous research on self-tracking—that was published between 2006 and 2019. The selection of journals and the use of a classification scheme were inspired by the comprehensive review of consumer wearable technology adoption from Kalantari (2017). Five databases (i.e., Web of Science, EBSCO, Science Direct, Springer Link, and Google Scholar) were used to search for articles in the self-tracking literature. After applying multiple inclusion and exclusion criteria, 55 empirical articles were identified as relevant to the present research.

Paper 2 and paper 3 collected primary data through six independent experiments on Amazon's Mechanical Turk (MTurk) between spring 2017 and spring 2019, with no overlap of participants across each experiment. In paper 2, curiosity is manipulated to examine (1) how incidental curiosity affects consumers' intention to obtain curiosity-irrelevant unknown information (Experiment 1); (2) what is the underlying mechanism of the proposed effect (Experiment 2); and (3) how incidental curiosity influences consumers' intention to use self-tracking products (Experiment 3). In paper 3, self-tracking is manipulated in effortful tasks to investigate (1) how self-tracking affects consumers' perceived competence based on gender (Experiment 1); (2) what is the effect of self-tracking on the task experience and underlying mechanism (Experiment 2); and (3) how self-tracking affects task experience when consumers overestimate themselves (Experiment 3). Table 1 provides a brief summary of the experiments conducted in paper 2 and paper 3, and Tables 2 and 3 describe key measurement items used in both papers.

Chapter 3: Table 1. Overview of experiments (paper 2 and paper 3)

		Independent variable (IV)	Manipulation (conditions)	Dependent variable (DV)	Number of participants (N)
Paper 2	Experiment 1	Curiosity	Curious vs. Incurious vs. Neutral	Time allocation in reading: familiar information vs. unknown information (curiosity-irrelevant)	128
	Experiment 2			Intention to read: familiar product vs. unknown product (curiosity-irrelevant)	212
	Experiment 3			Intention to purchase: non-tracking product vs. self-tracking product (curiosity-irrelevant)	190
Paper 3	Experiment 1	Self-tracking	Tracking vs. Not tracking	Perceived competence (riddle solving task)	222
	Experiment 2			Task experience (math solving task)	226
	Experiment 3		Tracking vs. Not tracking & Overestimation vs. Normal	Task experience (quiz solving task)	327

Chapter 3: Table 2. Key measurements in paper 2

Construct	Scale (reference)	Items
Curiosity	1 = strongly disagree, 7 = strongly agree (Wang & Huang, 2017)	1. At the current moment, how curious are you about the (e.g., answers to the riddles)? 2. At the current moment, how eagerly do you want to know the ___?
Perceived value of unknown information (curiosity-relevant/ curiosity-irrelevant)	1 = strongly disagree, 7 = strongly agree (Yang, Yu, Zo, & Choi, 2016)	1. Receiving information about the (e.g., upcoming content of the column) is important to me. 2. Receiving information about the ___ is meaningful to me. 3. Receiving information about the ___ delivers me good value. 4. Receiving information about the ___ is worthy of my time.

Chapter 3: Table 3. Key measurements in paper 3

Construct	Scale (reference)	Items
Perceived competence	1 = strongly disagree, 7 = strongly agree (Deci & Ryan, 2003)	1. I think I am pretty good at (e.g., riddles). 2. I think I did pretty well at ___. 3. I felt pretty competent after solving the ___ for a while. 4. I was pretty skilled at ___.
Enjoyment	1 = strongly disagree, 7 = strongly agree (Deci & Ryan, 2003)	1. I enjoyed solving the (e.g., riddles) very much. 2. The ___ were fun to solve. 3. I would describe these ___ as very interesting. 4. I thought these ___ were quite enjoyable.
Subjective vitality	1 = strongly disagree, 7 = strongly agree (Bostic, Rubio, & Hood, 2000)	1. Now that finished with (e.g., the riddle session), I feel alive and vital. 2. Now that finished with ___, I feel energized. 3. Now that finished with ___, I have energy and spirit. 4. Now that finished with ___, I feel awake and alert.

Chapter 4

4. Findings

This chapter summarizes the main findings of the literature review (section 4.1) and the two empirical papers (section 4.2 and section 4.3) conducted in the current dissertation.

4.1 Drivers and outcomes of fitness tracking: a systematic literature review

The research question addressed in this review (paper 1) aims to identify the drivers and outcomes of self-tracking behavior in physical activities, i.e., fitness tracking. Thus, 55 empirical research on self-tracking were reviewed and, as a result, 18 drivers of fitness tracking technology adoption were identified. These 18 drivers were then classified into four different categories: user characteristics, device characteristics, perceived benefits/risks, and external drivers. In addition, the review revealed four main outcomes of fitness tracking: task motivation, task/user experience, physical activity level, and well-being/health. This review also identified important gaps in the literature and suggested avenues for future research. For example, more research is needed to investigate the underlying drivers of the identified constructs (e.g., perceived value) that influence self-tracking behavior (e.g., adoption), as well as to clarify the seemingly contradicting findings in the literature regarding the effect of self-tracking on consumer experience (e.g., enjoyment).

4.2 Incidental curiosity as the driver of self-tracking behavior

The research question in this empirical study (paper 2) considers how incidental curiosity influences consumers' intention to use self-tracking products. Three experiments demonstrated that curiosity can prompt consumers' intention to obtain curiosity-irrelevant unknown information (e.g., unknown product information, unknown self-related information). This occurs because curiosity can enhance consumers' perceived value of curiosity-relevant unknown information, and this

positive perception of curiosity-relevant unknown information can spill over to curiosity-irrelevant unknown information. Therefore, by enhancing consumers' perceived value of the (curiosity-irrelevant) unknown self-related information that self-tracking products provide, incidental curiosity can increase consumers' intention to use self-tracking products.

4.3 The effects of self-tracking and gender on the experience of effortful tasks

The research question in the third paper examines the experiential side of self-tracking—the effect of self-tracking on task experience (i.e., enjoyment, subjective vitality). An experimental approach was taken to examine how self-tracking and gender influence consumer experience with effortful tasks. A series of three experiments demonstrated that, for effortful tasks, self-tracking has contrasting effects on the task experience of different consumer segments: for example, it has a positive effect on females, but a negative effect on males. This is because females (vs. males) tend to underestimate (vs. overestimate) themselves and are more likely to perceive self-tracking feedback as informational (vs. controlling). As a result, self-tracking feedback helps females realize that they are more capable than they originally thought, and thus has a more positive impact on females' (vs. males') perceived competence, which leads to more positive task experience for females (vs. males).

Chapter 5

5. General discussion

The current dissertation aims to enhance our understanding of the drivers and outcomes of consumers' self-tracking behavior. To achieve this goal, one literature review and two empirical studies are conducted. Paper 1 provides a systematic review of the extant research on fitness tracking behavior; paper 2 investigates incidental curiosity as a driver of consumer self-tracking behavior; and paper 3 examines the effects of self-tracking and gender on the overall experience of effortful tasks. In particular, the current dissertation offers the following contributions.

5.1 Theoretical contributions

The present dissertation contributes to the self-tracking literature by investigating the likely drivers and outcomes of self-tracking behavior. First, despite the increasing amount of research conducted on the topic of self-tracking, to the best of my knowledge, there has been no systematic review of the literature on consumer self-tracking behavior, particularly in regard to physical activity. As fitness is one of the fields where self-tracking technologies have been widely applied in real life, the current dissertation provides a timely review and integrative framework of the existing research on fitness tracking, as well as its drivers and outcomes. Specifically, paper 1 identifies 18 drivers of fitness tracking technology adoption and reveals four main outcomes of fitness tracking behavior. In addition, paper 1 addresses the theoretical and methodological limitations of the existing research on fitness tracking, and suggests possible avenues for future research.

Second, in response to the research gap identified in paper 1, paper 2 investigates curiosity as a potential driver of consumer self-tracking behavior, and reveals that incidental curiosity—as a situational factor—can increase consumers' intention to use self-tracking products. Paper 2 thus extends the previous findings on the drivers of self-tracking behavior beyond the factors that have been suggested by general innovation

adoption theories (e.g., TAM, UTAUT2). Paper 2 also enhances the self-tracking literature by directly investigating the causal relationship between self-tracking behavior and its driver—curiosity, as well as by offering explanations for the effect of curiosity on intention to use self-tracking products.

Third, paper 1 reveals that research that examines the effect of self-tracking on task experience is lacking. Paper 3 addresses this gap by empirically testing the effects of self-tracking and gender on the experience of effortful tasks. Paper 3 improves our current understanding of the effect of self-tracking on task experience by showing that self-tracking feedback has a positive impact on task experience for effortful tasks, especially for individuals who underestimate themselves (e.g., females). To the best of my knowledge, this study is the first to consider the role of individual and contextual factors when investing the effect of self-tracking on consumer experience.

Fourth, the current dissertation sheds light on the literature on consumer curiosity. While previous research has shown that curiosity prompts consumers to search for curiosity-relevant unknown information (Kruger & Evans, 2009; Marvin & Shohamy, 2016; Menon & Soman, 2002), the current dissertation suggests that incidental curiosity can also make consumers desire curiosity-irrelevant unknown information (e.g., unknown product information, unknown self-related information). This is because curiosity increases the perceived value of curiosity-irrelevant unknown information. Therefore, the current dissertation contributes to the field by investigating the relationship between curiosity and the perception of unknown information, as well as by offering empirical evidence for the proposed effect.

Lastly, the current dissertation contributes to the literature on consumer experience. While previous research has considerably focused on how consumer experience is affected by various contextual factors (e.g., ambient scent, physical environment; Cirrincione, Estes, & Carù, 2014; Kumar, Dash, & Malhotra, 2018), the current dissertation finds that self-tracking—as a feedback mechanism—is an important marketing tool that can influence consumers' task experience. This finding thus adds to the existing constellation of external stimuli that can positively affect consumer

experience. In summary, this paper contributes to both consumer researchers and marketing practitioners by integrating a wide body of research on an important consumer behavior topic and by offering broad avenues for further research.

5.2 Practical implications

The current dissertation also provides important practical implications. First, the current dissertation identifies multiple product-related factors that facilitate the adoption of fitness tracking technologies. Notably, several of these factors, such as data quality, usefulness, and aesthetics, are important for not only fitness tracking technologies but also other self-tracking technologies in general. For example, it is expected that individuals would care about the quality of data regarding their sleep just as much as the quality of data regarding their level of physical activity. Therefore, the findings presented in the current dissertation can help designers and manufacturers of various self-tracking products improve the features and desirability of their products to better address consumer needs.

Second, curiosity is found to be a situational factor that can improve consumers' desire to use self-tracking products. As curiosity can increase consumers' perceived value of the unknown information that self-tracking products provide, one possible strategy for marketers is to induce consumers' curiosity inside the store (e.g., showing a puzzle on a display screen). Marketers can also present self-tracking products to consumers who are in a curious state (e.g., show the advertisement right after an interesting movie trailer). In this way, marketers can utilize both product-related factor and situational factor identified in this dissertation to facilitate the adoption or use of self-tracking technologies. In addition, the findings of the current dissertation provide useful insights for the marketers of innovative but incongruent products (e.g., gene-modified food): by inducing consumers' curiosity, marketers can prompt consumers to acquire unknown information about an incongruent product, which would help consumers better understand the benefits of the product, and thus make them more likely to adopt the product.

Lastly, the current dissertation examines the outcomes of fitness tracking behavior, and finds that fitness tracking can be an effective way to improve consumers' task motivation, activity level, and health. Thus, marketers of fitness tracking technologies (e.g., activity trackers, apps) should appeal to consumers by using persuasive language to communicate the effectiveness and benefits of their products. However, firms for whom consumer enjoyment matters (e.g., sports center) should be cautious about implementing self-tracking technologies, as self-tracking may reduce consumer enjoyment, depending on the types of activities that are tracked and the types of consumers who use it. Nevertheless, the current dissertation shows that self-tracking is more likely to induce positive consumer experience when consumers are engaged in effortful tasks, especially for those who tend to underestimate their competence (e.g., females). Therefore, marketers of self-tracking technologies should employ more context-based strategies to address different types of consumers to optimize their marketing performance and consumer outcomes.

Chapter 6

6. Limitations and avenues for future research

It is important to note the limitations of this dissertation and to suggest avenues for future research. First, the current dissertation identifies one situational factor (i.e., incidental curiosity) as an underlying driver of one of the constructs (i.e., perceived value) suggested by general innovation adoption theories such as UTAUT2, which can facilitate the adoption of self-tracking technologies. Future research should thus explore potential drivers of other constructs (e.g., perceived ease of use) that may also increase self-tracking technology adoption. In addition, researchers should investigate consumer adoption of self-tracking technologies by measuring consumers' actual behavior rather than their behavioral intention, as intention does not always lead to behavior.

Second, in terms of the outcomes of self-tracking behavior, there is a lack of research that empirically tests the effects of self-tracking technologies on task experience (e.g., enjoyment), and the existing findings in the literature are inconclusive (e.g., positive vs. negative effect). The current dissertation identifies one situational context (i.e., effortful tasks) and one individual characteristic (i.e., gender) that can lead to a positive effect of self-tracking on task experience. Future research can therefore contribute to the field of self-tracking by investigating other possible boundary conditions for the effects of self-tracking on consumer outcomes (e.g., motivation, experience).

Lastly, care should be taken when generalizing the results of the experiments conducted in this dissertation (e.g., MTurk sample). Future research should attempt to validate these results by, for example, replicating the studies conducted herein within various contexts and using different populations to provide more insights (e.g., causal mechanisms) into the relationship between self-tracking and its drivers and outcomes. I hope these suggestions merit future research on self-tracking and related topics.

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Paper 1

Paper 1: Consumer self-tracking behavior in physical activity: an integrative review of drivers and outcomes of fitness tracking, under review at *Sensors*

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Abstract

Advances in technologies (e.g., smartphones, wearables) have resulted in the concept of "self-tracking", and the use of self-tracking technologies in physical activities (i.e., fitness tracking) is on the rise. For example, many consumers track and monitor their fitness-related metrics (e.g., steps walked, distance ran, and calories burned) to change their behavior or keep themselves active. Despite the widespread application of self-tracking technologies in fitness, relatively little is known about its drivers and outcomes. To address this gap, the current paper provides an overview of the literature on self-tracking with a focus on the drivers and outcomes of fitness tracking behavior, and offers four important contributions. First, it identifies 18 drivers of fitness tracking technology adoption. Second, it discusses four main outcomes of fitness tracking behavior, and provides a framework for future testing. Third, by drawing on existing studies conducted across various fitness tracking technologies (e.g., fitness trackers, apps) and user groups (e.g., patients, seniors, and females), it provides valuable insights that can be generalizable to other settings (e.g., other types of users and fitness tracking products). Finally, the current paper provides important practical implications and addresses avenues for future research.

Keywords

Adoption, experience, fitness tracking, literature review, motivation, well-being

1. Introduction

In recent years, it has become remarkably easy to keep records of everyday life (Jarrahi, Gafinowitz, & Shin, 2018). Advances in technologies (e.g., smartphones, wearables) have made it possible for consumers to monitor and track almost every sphere of their lives (Ajana, 2018). From daily activities such as walking, eating, and sleeping to mood and health, consumers now have access to more information about themselves than ever before (Etkin, 2016). This phenomenon is referred to as self-tracking (or self-quantification)—using modern technologies to automatically track and collect personal information in numbers (Ajana, 2018), and self-tracking is now a common practice in the lives of many consumers (Epstein et al., 2016).

The increasing tendency for individuals to collect their personal data was spotted in 2007, and since then the trend of self-tracking has grown steadily across the globe (Sjöklint, Constantiou, & Trier, 2013). As self-tracking allows consumers to collect data about themselves automatically (or with less effort), it has been utilized in many different practices, such as fitness, healthcare, and medical care. Particularly, there has been a growing interest in the use of self-tracking technologies in physical activities, namely fitness tracking, with an increasing number of research devoted to this topic (e.g., Attig & Franke, 2018; Canhoto & Arp, 2017; Stiglbauer, Weber, & Batinic, 2019). For example, a number of studies have explored the motivational and behavioral impacts of fitness tracking on consumers (e.g., Butryn, Arigo, Raggio, Colasanti, & Forman, 2016; Pettinico & Milne, 2017), while others have looked at the drivers (e.g., individual differences, product quality) of fitness tracking technology adoption (e.g., Jarrahi et al., 2018; Schall Jr, Sesek, & Cavuoto, 2018). Such research demonstrates various drivers and outcomes of fitness tracking.

Recent work such as that by Kalantari (2017) has provided a review of the literature on wearable technology adoption. Although such an investigation suggests several important factors (e.g., technology characteristics, individual characteristics) that can influence wearable technology adoption, the drivers of self-tracking technology (in this case, fitness tracking technology) adoption may not necessarily be the same. First, not

all wearables have the fitness tracking functionality. For example, devices such as head-mounted displays and smart glasses are wearables, but they often do not have fitness tracking features. Second, some wearables do more than just fitness tracking. For example, a smartwatch may allow basic fitness tracking (e.g., step count), but it is more than a fitness tracker, as fitness tracking is only one of the features it has (e.g., calling, texting, gaming, and web browsing). Consumers may thus adopt wearables for reasons other than fitness tracking itself. Therefore, although wearables are an important concept in the investigation of consumer fitness tracking behavior, care should be taken in generalizing the findings on wearable technology adoption to the domain of fitness tracking technology adoption.

Other works such as that by Cheatham, Stull, Fantigrassi, and Motel (2018) and that by Almalki, Gray, and Martin-Sanchez (2016) have reviewed the literature regarding the effects of self-tracking technologies in medical sector (e.g., effects on patients' health condition). However, limited attention has been paid to the effects of self-tracking, particularly fitness tracking, on other consumer outcomes (e.g., motivation, experience), especially among general population (e.g., regular consumers).

To the best of the authors' knowledge, there has been no systematic review of the literature on consumer fitness tracking behavior. A synthesized summary of the earlier research thus can provide value for both academics and practitioners, as it would help identify the likely drivers and outcomes of fitness tracking behavior. The aim of the current paper is therefore to provide a comprehensive review of a diverse range of contemporary literature that informs our understanding of the drivers and outcomes of fitness tracking behavior.

By systemizing the findings and conclusions of the existing studies on fitness tracking, the current paper makes four important contributions. First, the current paper adds to the literature on self-tracking behavior by exploring and summarizing the drivers of self-tracking behavior in physical activity—fitness tracking. Second, along with the drivers, the current paper investigates the potential outcomes of fitness tracking behavior, and the inclusion of both drivers and outcomes enables the development of an integrative

framework of fitness tracking behavior and suggests directions for future research. Third, by drawing on the existing studies on fitness tracking, which have been conducted across various fitness tracking technologies (e.g., armband, pedometer, and app) and user groups (e.g., patients, seniors, and students), the current paper provides valuable insights that can be generalizable to other settings (e.g., other types of users and fitness tracking products). Lastly, the current paper deepens the knowledge managers require to improve their products and marketing strategies (e.g., segmentation) to facilitate the adoption of fitness tracking technologies (e.g., fitness trackers) among consumers. The findings of the current paper also provide important insights for firms (e.g., gyms, sports centers) that may benefit from improving consumer motivation, experience, or activity level in fitness.

The current paper is organized as follows. First, the authors discuss the research method of the current review. Second, they present an overview of the drivers of fitness tracking technology adoption. Third, the outcomes of fitness tracking behavior are discussed, along with the roles of relevant moderating and mediating variables. Lastly, a summary and suggestions for future research are provided.

2. Literature review method

2.1 Search strategy

A systematic review of the literature was conducted using the following method. First, the authors identified two review questions: 1) what factors drive consumer adoption (or use) of fitness tracking technologies? and 2) how fitness tracking affects consumers (e.g., physical and psychological outcomes)? Then, the authors selected multiple search terms to guide their search. The keyword “self-tracking” was used as the primary search string. The authors also used other search terms that are analogous to the term “self-tracking” (e.g., “self-quantification”, “self-monitoring”, and “tracking”), relevant to physical activity (e.g., “fitness tracking”, “activity tracking”), and specific to fitness tracking (e.g., “pedometer”, “fitness tracker”, and “activity tracker”). The focus of the search was exclusively within peer-reviewed journal articles and conference

proceedings from a range of international sources, using databases Web of Science, EBSCO, Science Direct, Springer Link, and Google Scholar. The authors further searched the references of the papers identified in the initial search.

2.2 Inclusion and exclusion criteria

To select appropriate papers for the current review, the authors read titles, abstracts, and findings of the searched papers, and applied a number of inclusion criteria. First, the selected papers had to include empirical evidence related to the drivers or outcomes of self-tracking behavior. Second, the selected papers had to investigate the drivers or outcomes of self-tracking behavior specifically in the context of physical activity (i.e., fitness tracking). Third, the selected papers had to have a clear focus on the fitness tracking feature of the focal technology or device (e.g., wearables or personal informatics), rather than other features (e.g., pointification [1], gamification [2]) or a combination of different features as a whole. The reason for the latter is that with a multifaceted technology, it is difficult to determine whether fitness tracking is the specific component that is contributing to the adoption or outcomes of fitness tracking. Lastly, as the trend of self-tracking emerged in 2007 (Sjöklint et al., 2013), the authors selected papers that were published after (including) 2006.

[1] Pointification refers to a process involving individuals collecting digital points through a scoring system (Sjöklint et al., 2013). For example, consumers receive points for being a member of a loyalty program (e.g., airlines, grocery stores, or movie theaters). Self-tracking involves pulling numbers from the users while pointification emphasizes pushing numbers from the scoring system to the users (Sjöklint et al., 2013). In the context of physical activities, self-tracking is more of an objective measure of one's behavior (e.g., number of steps and distance walked) while pointification is a subjective measure of one's performance (e.g., 10 points for each step made), which does not represent one's objective behavioral output. As a result, in self-tracking the user is actively seeking numbers while in pointification numbers are provided to the user without necessarily the user's intention to seek the numbers (Sjöklint et al., 2013).

[2] Gamification is a process of making activities more game-like by using game elements (e.g., points, badges, and leaderboards) into non-gaming contexts (Huotari & Hamari, 2016). Self-quantification (or self-tracking) is one fundamental mechanism of gamification, and fitness trackers can be viewed as a prototypical example for a gamified application (Attig & Franke, 2018). Many fitness trackers in fact have incorporated various game elements, such as reward and badges, and thus effort should be made to separate the effect of self-tracking from the effect of other game elements implemented in the device.

In this round, exclusion criteria were as follows. First, the authors eliminated the papers that focused purely on the technical design or usage situation of fitness tracking technologies (e.g., which function do users like). Second, the authors excluded the papers examining the reliability and validity of fitness tracking technologies. Third, they also eliminated the papers that provided limited evidence when investigating the outcomes of fitness tracking (e.g., lack of neutral control condition or lack of baseline measure). Lastly, the authors excluded the studies that implemented non-automatic tracking (e.g., manual logging of fitness data), as automatic tracking is one of the most important features of modern fitness tracking technologies.

2.3 Selection summary

By the end of the selection process, the authors identified 55 empirical papers as relevant for the current review. This number reflects the emergent nature of the topic. Of these, 37 were from peer-reviewed journals, and 18 were from conference proceedings. Twenty-seven of the papers investigated the drivers of fitness tracking technology adoption, while 41 papers examined the outcomes of fitness tracking. The timeframe of the selected papers ranged across a 13-year period from 2006 to 2019 (with a peak of work between 2014 and 2017), covering a variety of fitness tracking technologies (e.g., Fitbit, Nike +, pedometer, and apps) and user groups (e.g., patients, seniors, adults, and students).

After selecting the papers, the authors manually conducted content analysis, and extracted and summarized critical data such as key findings and methodological features of the selected papers. In addition, the authors created a list of key factors by identifying major constructs and sub-constructs explored in the selected papers. This list served as a basis for developing a framework through which the authors analyzed the literature.

3. Drivers of fitness tracking

In this section, the authors provide an overview of the 18 drivers of fitness tracking technology adoption identified in the literature. The authors classify these drivers into four different categories: user characteristics, device characteristics, perceived

benefits/risks, and external drivers. See Appendix A for a full summary of the literature empirically testing these drivers.

3.1 User characteristics

3.1.1 Age

Not all consumers exhibit the same tendency for the adoption of innovative technologies (Kalantari, 2017). Previous research has identified age as an influential factor of fitness tracking technology adoption. For example, Rupp, Michaelis, McConnell, and Smither (2018) have found that age influences consumers' desire to use fitness trackers. Their results indicate that older people are less likely to adopt or use fitness tracking technologies, as they have low perceived usability (e.g., easy to use, comfort) of such technologies.

3.1.2 Personality traits

Personality traits are another group of variables that can influence consumer adoption of fitness tracking technologies. According to Rupp et al. (2018), certain personality traits (i.e., agreeableness [3], conscientiousness [4], and extraversion [5]) can affect consumers' desire to use fitness trackers by influencing their perceived device usability and perceived motivational affordances (i.e., autonomy [6], competence [7], and relatedness [8] need satisfaction). For example, extraverted individuals have high intention to use fitness trackers, as they perceive these devices as highly usable and

[3] Agreeable people are more trusting and less suspicious of others (Rupp et al., 2018).

[4] Greater conscientiousness is associated with greater planning ability, goal achievement, decision-making efficiency, working memory skills, and health and fitness behaviors (Rupp et al., 2018).

[5] Greater extroversion is associated with being more social and outgoing, and extraverts (vs. introverts) are more likely to seek opportunities for stimulation and interaction that exist outside of themselves and are more likely to exercise (Rupp et al., 2018).

[6] Autonomy is the need to make meaningful choices and be in control (Rupp et al., 2018).

[7] Competence is the need to be skillful, effective, meet challenges, and achieve goals (Rupp et al., 2018).

[8] Relatedness is the need to feel connected to others and have social support (Rupp et al., 2018).

motivating, and conscientious or agreeable individuals also have high intention to use fitness trackers, as they find these devices providing high motivational affordances. On the other hand, Attig and Franke (2018) have not found significant direct effects of the Big Five personality traits (e.g., extraversion, conscientiousness, agreeableness, and neuroticism) on consumers' motivation to use fitness trackers. These findings indicate indirect effects of personality traits on fitness tracking technology adoption.

3.1.3 Technology affinity/self-efficacy

Previous research has identified consumers' affinity and self-efficacy in technology as important drivers of fitness tracking technology adoption (e.g., Attig & Franke, 2018; Gao, Li, & Luo, 2015; Rupp et al., 2018). For example, affinity for technology—the tendency of an individual to actively explore (new) technologies—is positively related to an individual's motivation to use a fitness tracker (Attig & Franke, 2018). Studies on technology self-efficacy also confirm the positive relationship between technology self-efficacy—an individual's judgement of his or her capability to use a technology to attain desired performance, rather than the actual skills that one has (Kalantari, 2017)—and fitness tracker adoption (Gao et al., 2015; Rupp et al., 2018).

3.1.4 Desire for feedback

Hope of success and need for cognitive closure address individuals' desire for feedback. For example, people with high hope of success would appreciate information (or feedback) about their task performance, as they believe that they can succeed in the task (Schüler, 2007). People with high need for cognitive closure would want to receive feedback (e.g., clear-cut answers) due to their desire to avoid ambiguous situations (Webster & Kruglanski, 1994). Both hope of success and need for cognitive closure are found to be positively associated with individuals' motivation to use a fitness tracker (Attig & Franke, 2018).

3.1.5 Product involvement

Another user characteristic considered as an important driver of adoption behavior is the product involvement. Product involvement refers to the interest a consumer has in

a product, which depends on how much one perceives the product to be personally relevant (Kalantari, 2017). Several researchers have found that lack of interest in fitness trackers is the reason why consumers are not purchasing them (e.g., Choe, Lee, Lee, Pratt, & Kientz, 2014; Mercer et al., 2016). In addition, low product involvement (e.g., low attachment to a fitness tracker) would even make consumers abandon a fitness tracker (Clawson, Pater, Miller, Mynatt, & Mamykina, 2015; Jarrahi et al., 2018). On the other hand, consumers are more likely to adopt (or use) a fitness tracker (e.g., Fitbit) when they have a general interest in the technology or are curious about the technology and personal data (Canhoto & Arp, 2017; Harrison, Marshall, Bianchi-Berthouze, & Bird, 2015; Jarrahi et al., 2018; Lazar, Koehler, Tanenbaum, & Nguyen, 2015; Shin, Cheon, & Jarrahi, 2015; Whooley, Ploderer, & Gray, 2014).

3.1.6 Current individual status (goal, motivation, and activity level)

Previous research has found that consumers are more likely to adopt or purchase a fitness tracker (e.g., Fitbit, Jawbone Up, and Nike +) when they have specific goals in mind, such as health goals, exercise goals, or self-improvement goals (e.g., Canhoto & Arp, 2017; Chang, Lu, Yang, & Luarn, 2016; Choe et al., 2014; Karapanos, Gouveia, Hassenzahl, & Forlizzi, 2016; Whooley et al., 2014). For example, consumers are more likely to adopt (or use) a fitness tracker when they have a goal or relatively strong motivation to become more active (Harrison et al., 2015; Jarrahi et al., 2018). User motivation thus is an important driver of fitness tracker adoption, and consumers would not use such a device when they have no need for it (Kim, 2014; Seiler & Hüttermann, 2015) or are already strongly motivated to maintain their physical activities (Jarrahi et al., 2018). Another factor that is related to individual status is one's current activity level. According to Rupp et al. (2018), consumers who are more physically active have higher desire to use a fitness tracker, as they are more likely to find such a device motivating.

Table 1 presents a summary of the papers that have studied the role of user characteristics in driving consumer adoption of fitness tracking technologies.

Paper 1: Table 1. Summary of the papers that studied user characteristics

			User characteristics					
Study	Method	Sample (mean age)	Age	Personality trait	Technology affinity/self-efficacy	Desire for feedback	Product involvement	Current individual status
Attig and Franke (2018)	Survey	N = 210 Actual users, 92.4% F (24)		√	√	√		
Jarrahi et al. (2018)	Interview	N = 29 University staff, actual users, 65.5% F					√	√
Rupp et al. (2018)	Survey	N = 103 Novice users, 53.4% F (36.5)	√	√	√			√
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)					√	√
Chang et al. (2016)	Interview Focus group	N = 15 Taiwan Executive MBA student, 60% users, 73.3% M (median 45)						√
Karapanos et al. (2016)	Survey (MTurk)	N = 133 Actual users, 65% M (median 30)						√
Mercer et al. (2016)	Focus group	N = 32 Patients, 72% F (64)					√	
Clawson et al. (2015)	Content analysis	N = 427 Posts on Craigslist site					√	
Gao et al. (2015)	Survey	N = 462 Actual user, 53.7% F (32)			√			
Harrison et al. (2015)	Survey Interview	N = 24 66.7% current users (vs. abandoned users), 54.2% F (18-55)					√	√
Lazar et al. (2015)	Interview	N = 17 Employees, 76.5% M (18-59)					√	
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)						√
Shin et al. (2015)	Focus group Interview	N = 15 Actual users					√	
Choe et al. (2014)	Content analysis	N = 52 Video posts on Quantified-self blog					√	√
Kim (2014)	Survey Focus group	N = 18 Student, F (20-29)						√
Whooley et al. (2014)	Content analysis	N = 51 Video posts on quantifiedself.com					√	√

Note: M refers to male, F refers to female. √ shows which user characteristics were tested in each study.

3.2 Device characteristics

3.2.1 Device quality

Like most products, product quality plays an important role in driving consumer adoption of fitness tracking technologies. Previous research has confirmed the importance of device quality (e.g., battery durability, sensor durability, or comfort) in facilitating consumers' use and adoption of fitness trackers (e.g., Coorevits & Coenen, 2016; Gao et al., 2015; Harrison et al., 2015; Kalantari, 2017; Kim, 2014; Schall Jr et al., 2018). For example, consumers do not use a fitness tracker that has insufficient quality (Seiler & Hüttermann, 2015), and they will abandon the device when it has technical problems (e.g., error), high frequency of maintenance, or is uncomfortable to wear (Clawson et al., 2015; Lazar et al., 2015; Shih, Han, Poole, Rosson, & Carroll, 2015).

3.2.2 Data quality

Another important aspect of fitness tracking technologies, which can influence consumer adoption, is the quality of collected personal data (e.g., accuracy, reliability). Previous research has shown that consumers abandon fitness trackers because of the poor data accuracy and reliability (e.g., Coorevits & Coenen, 2016; Epstein et al., 2016; Harrison et al., 2015; Shih et al., 2015). The quality of data offered by fitness trackers (e.g., Fitbit) matters, because consumers want to ensure that the collected data effectively and precisely represent their personal and health-related concerns (Jarrahi et al., 2018). Preusse, Mitzner, Fausset, and Rogers (2017) also have found that inaccurate data decreases the perceived usefulness of fitness trackers, and thus is one of the main barriers to the adoption of fitness trackers.

3.2.3 Device attractiveness/novelty

Many researchers have found device attractiveness and novelty to be important drivers of fitness tracking technology adoption. Device attractiveness refers to the aesthetic design of a product, such as shapes, colors, materials, and user interfaces (Yang, Yu, Zo, & Choi, 2016). Previous research has found that consumers are influenced by the design,

style, and appearance (e.g., look and feel) of fitness trackers when making adoption decisions (e.g., Canhoto & Arp, 2017; Chang et al., 2016; Coorevits & Coenen, 2016; Karapanos et al., 2016; Kim, 2014). Consumers thus would not use a fitness tracker when the device does not aesthetically look good (Harrison et al., 2015; Shih et al., 2015). Device novelty, defined as the newness of a technology or design (Tatikonda & Rosenthal, 2000), has also been found to be a compelling motivator for consumers to adopt or use fitness trackers (Kim, 2014; Lazar et al., 2015). For example, consumers tend to abandon fitness trackers when the novelty of such devices wears off (Jarrahi et al., 2018) or when they feel that the device does not provide new information anymore (Epstein et al., 2016).

3.2.4 Device functionality

Other device related factors that have been identified as important for the adoption of fitness trackers are persuasiveness (e.g., effective nudging), customizability (e.g., personalization), tracking ability (e.g., number of functionalities), and distraction from the focal activity (Coorevits & Coenen, 2016; Kim, 2014; Randriambelonoro, Chen, & Pu, 2017; Shih et al., 2015).

Table 2 presents a summary of the papers that have studied device characteristics in relation to consumer adoption of fitness tracking technologies.

Paper 1: Table 2. Summary of the papers that studied device characteristics

			Device characteristics			
Study	Method	Sample (mean age)	Device quality	Data quality	Device attractiveness/novelty	Device functionality
Jarrahi et al. (2018)	Interview	N = 29 University staff, actual users, 65.5% F		√	√	
Schall Jr et al. (2018)	Survey	N = 952 Engineers, 70.4% M (48.7)	√			
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)			√	
Preusse et al. (2017)	Interview	N = 16 50% F (70)		√		
Randriambelonoro et al. (2017)	Interview	N = 18 Swiss patients, 61.1% F (36-73)				√
Chang et al. (2016)	Interview Focus group	N = 15 Taiwanese Executive MBA students, 60% user, 73.3% M (median 45)			√	
Coorevits and Coenen (2016)	Content analysis	N = 93 Comments on Reddit site	√	√	√	√
Epstein et al. (2016)	Survey & Interview	N = 193 56.5% M (31.6) & N = 12 66.7% F		√		
Karapanos et al. (2016)	Survey (MTurk)	N = 133 Actual users, 65% M (median 30)			√	
Clawson et al. (2015)	Content analysis	N = 427 Posts on Craigslist site	√			
Gao et al. (2015)	Survey	N = 462 Actual users, 53.7% F (32)	√			
Harrison et al. (2015)	Survey Interview	N = 24 66.7% current users (vs. abandoned users), 54.2% F (18-55)	√	√	√	
Lazar et al. (2015)	Interview	N = 17 Employees, 76.5% M (18-59)	√		√	
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)	√			
Shih et al. (2015)	Survey	N = 26 Students, 69.2% M (20-24)	√	√	√	√
Kim (2014)	Survey Focus group	N = 18 Students, F (20-29)	√		√	√

Note: M refers to male, F refers to female. √ shows which device characteristics were tested in each study.

3.3 Perceived benefits/risks

3.3.1 Perceived ease of use

The effect of perceived ease of use (PEOU) on the behavioral intention to use fitness tracking technologies has been widely studied and confirmed in the literature. PEOU is defined as the degree to which an individual believes that using a particular product would be free of effort (Kalantari, 2017). Previous research has found that PEOU (e.g., automatic tracking) has a positive impact on the adoption of fitness trackers (e.g., Coorevits & Coenen, 2016; Gao et al., 2015; Kim, 2014; McMahon et al., 2016; Mercer et al., 2016; Preusse, Mitzner, Fausset, & Rogers, 2014; Preusse et al., 2017). For example, an easy access to personal data is an important driving force of fitness tracker adoption (Canhoto & Arp, 2017; Jarrahi et al., 2018). On the contrary, consumers would abandon fitness trackers (e.g., Fitbit One) when they cannot comfortably interact with the device (e.g., complex device, lack of expertise to interpret the data) (Clawson et al., 2015; Lazar et al., 2015; Randriambelonoro et al., 2017; Seiler & Hüttermann, 2015).

3.3.2 Perceived usefulness

Similar to PEOU, perceived usefulness (PU) also exerts a significant effect on intention to use fitness tracking technologies. PU is defined as the degree to which an individual believes that using a particular product would enhance his or her performance (Kalantari, 2017). Previous research has confirmed the positive effect of PU (e.g., viewing progress over time) on the adoption of fitness trackers (e.g., Kim, 2014; McMahon et al., 2016; Mercer et al., 2016; Preusse et al., 2014, 2017). For example, Rupp et al. (2018) have found that device usability is positively associated with the intention to use a fitness tracker. On the other hand, consumers show low interest in using fitness trackers when the utility of the device is perceived as insufficient (e.g., feel

no need for the information, low performance expectancy[9]) or when the device does not deliver what is expected by consumers (Clawson et al., 2015; Gao et al., 2015; Lazar et al., 2015; Seiler & Hüttermann, 2015).

3.3.3 Perceived enjoyment

Perceived enjoyment is defined as the extent to which the activity of using a specific technology is perceived to be enjoyable in its own right, aside from any performance consequences of using such a technology (Kalantari, 2017). Previous research has identified perceived enjoyment (or playfulness) as a powerful predictor of the adoption of fitness tracking technologies (e.g., Randriambelonoro et al., 2017; Rheingans, Cikit, & Ernst, 2016). The pleasure or enjoyment derived from adopting and using a fitness tracker affects consumers' intention to adopt the device, suggesting that consumers pay attention to the pleasure-bringing aspects of fitness tracking technologies when deciding whether or not to accept them (Gao et al., 2015; Gimpel, Nißen, & Görlitz, 2013).

3.3.4 Perceived device value

Perceived value refers to consumer's overall assessment of the utility of a product based on the perception of what is received (e.g., benefits) and what is given (e.g., costs) (Kalantari, 2017). In the literature, perceived value (e.g., benefits minus costs) has been proven to drive the favorable intention to adopt fitness trackers (e.g., Canhoto & Arp, 2017; Clawson et al., 2015; Schall Jr et al., 2018). For example, Gualtieri, Rosenbluth, and Phillips (2016) have found that the perceived value of a fitness tracker is positively related to its acceptability or adoption. Other studies have incorporated the cost construct (e.g., monetary cost, user effort) in their investigation, and showed a negative effect of cost on consumers' decision to adopt fitness trackers (Epstein et al., 2016; Gualtieri et al., 2016; Mercer et al., 2016).

[9] Performance expectancy is defined as the degree to which adopting a technology will bring effectiveness to users in performing certain activities (Gao et al., 2015).

3.3.5 Perceived risk

Perceived risk is defined as an individual's uncertainty about the potential positive and negative consequences of his or her purchase decision (Kalantari, 2017). The literature on fitness tracking technology adoption extensively discusses the privacy concerns of consumers, and privacy risk has been identified as an important barrier to the adoption of fitness tracking technologies. Privacy risk in fitness tracking emphasizes the extent to which a person believes that using a fitness tracker has negative consequences for his or her privacy (e.g., loss of control over personal information) (Rheingans et al., 2016). Previous research has found that privacy is one of the most frequently mentioned concerns regarding the adoption of fitness trackers (e.g., Chang et al., 2016; Randriambelonoro et al., 2017; Schall Jr et al., 2018). Epstein et al. (2016) and Gao et al. (2015) have also suggested that perceived privacy risk negatively affects individuals' intention to adopt fitness trackers. However, Rheingans et al. (2016) have not found a significant impact of perceived privacy risk on intention to use fitness trackers among young population (average age of 26). Thus, there is a need for further research to investigate the potential moderating role of age on the relationship between perceived privacy risk and fitness tracking technology adoption.

Table 3 presents a summary of the papers that have studied perceived benefits/risks to understand consumer adoption of fitness tracking technologies.

Paper 1: Table 3. Summary of the papers that studied perceived benefits/risks

			Perceived benefits/risks				
Study	Method	Sample (mean age)	Perceived ease of use	Perceived usefulness	Perceived enjoyment	Perceived device value	Perceived risk
Jarrahi et al. (2018)	Interview	N = 29 University staff, actual users, 65.5% F	√				
Rupp et al. (2018)	Survey	N = 103 Novice users, 53.4% F (36.5)		√			
Schall Jr et al. (2018)	Survey	N = 952 Engineers, 70.4% M (48.7)				√	√
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)	√			√	
Preusse et al. (2017)	Interview	N = 16 50% F (70)	√				
Randriambelonoro et al. (2017)	Interview	N = 18 Swiss patients, 61.1% F (36-73)	√	√	√		√
Chang et al. (2016)	Interview Focus group	N = 15 Taiwanese Executive MBA students, 60% user, 73.3% M (median 45)					√
Coorevits and Coenen (2016)	Content analysis	N = 93 Comments on Reddit site	√				
Epstein et al. (2016)	Survey & Interview	N = 193 56.5% M (31.6) & N = 12 66.7% F				√	√
Gualtieri et al. (2016)	Interview	N = 10 Patients, 80% F (61)				√	
McMahon et al. (2016)	Interview	N = 95 Seniors, 75% F (79.8)	√	√			
Mercer et al. (2016)	Focus group	N = 32 Patients, 72% F (64)	√	√		√	
Rheingans et al. (2016)	Survey	N = 115 Germans, 53.9% F (25.9)			√		√
Clawson et al. (2015)	Content analysis	N = 427 Posts on Craigslist site	√	√		√	
Gao et al. (2015)	Survey	N = 462 Actual users, 53.7% F (32)	√	√			√
Lazar et al. (2015)	Interview	N = 17 Employees, 76.5% M (18-59)	√	√			
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)	√	√			
Kim (2014)	Survey Focus group	N = 18 Students, F (20-29)	√	√			
Preusse et al. (2014)	Interview	N = 16 Seniors, 50% F (70)	√	√			
Gimpel et al. (2013)	Survey	N = 150 Actual users, 33% patient, 58% M (34)			√		

Note: M refers to male, F refers to female. √ shows which perceived benefits/risks were tested in each study.

3.4 External drivers

3.4.1 Social influences

Previous research has found that social influences (e.g., social expectation, social support, social connection, word-of-mouth, or social media) can affect fitness tracker adoption (e.g., Canhoto & Arp, 2017; Chang et al., 2016; Gao et al., 2015; Seiler & Hüttermann, 2015; Yang et al., 2016). A number of researchers have also confirmed that social comparison (e.g., competition) is an important factor that affects the use and adoption of fitness trackers (e.g., Coorevits & Coenen, 2016; Gimpel et al., 2013; Harrison et al., 2015; Kim, 2014). For example, consumers would abandon fitness trackers when the device does not support their desire to compete with their friends (Clawson et al., 2015; Shih et al., 2015). These findings indicate that consumers wish to see better support for sharing and comparing their fitness data with others.

3.4.2. Financial incentives

Another external driver that has been identified in the literature is financial incentive. For example, financial incentives or rewards such as discounts on insurance, rebates on fitness club membership, or employee subsidies can help facilitate fitness tracker adoption (Canhoto & Arp, 2017; Seiler & Hüttermann, 2015).

3.4.3 Special situations

In addition to the aforementioned factors, researchers have identified some special situations that can influence consumer adoption of fitness tracking technologies, which include allergic reactions, availability of alternative devices, owning a similar device, forgetting to wear or losing a device, or changes in life circumstances (e.g., injury, health status, or job), etc. These situations can all lead to abandoning of fitness trackers (Clawson et al., 2015; Coorevits & Coenen, 2016; Epstein et al., 2016; Gualtieri et al., 2016; Harrison et al., 2015; Shih et al., 2015).

Table 4 presents a summary of the papers that have studied the role of external drivers in predicting consumer adoption of fitness tracking technologies.

Paper 1: Table 4. Summary of the papers that studied external drivers

			External drivers		
Study	Method	Sample (mean age)	Social influence	Financial incentive	Special situation
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)	√	√	
Chang et al. (2016)	Interview Focus group	N = 15 Taiwanese Executive MBA students, 60% user, 73.3% M (median 45)	√		
Coorevits and Coenen (2016)	Content analysis	N = 93 Comments on Reddit site	√		√
Epstein et al. (2016)	Survey & Interview	N = 193 56.5% M (31.6) & N = 12 66.7% F			√
Gualtieri et al. (2016)	Interview	N = 10 Patients, 80% F (61)			√
Clawson et al. (2015)	Content analysis	N = 427 Posts on Craigslist site	√		√
Gao et al. (2015)	Survey	N = 462 Actual users, 53.7% F (32)	√		
Harrison et al. (2015)	Survey Interview	N = 24 66.7% current users (vs. abandoned users), 54.2% F (18-55)	√		√
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)	√	√	
Shih et al. (2015)	Survey	N = 26 Students, 69.2% M (20-24)	√		√
Kim (2014)	Survey Focus group	N = 18 Students, F (20-29)	√		
Gimpel et al. (2013)	Survey	N = 150 Actual users, 33% patient, 58% M (34)	√		

Note: M refers to male, F refers to female. √ shows which external drivers were tested in each study.

4. Outcomes of fitness tracking

In this section, the authors discuss the outcomes of fitness tracking that have been identified by reviewing the literature on fitness tracking behavior. The main outcome variables identified are: task motivation, task experience, physical activity, and well-being/health. The authors also discuss the possible moderators (e.g., boundary conditions) and mediators (e.g., process evidence) in relation to the effects of fitness tracking on its outcomes. A full summary of the literature supporting (e.g., empirically tested) the outcomes of fitness tracking can be found in Appendix B.

4.1 Task motivation

The relationship between fitness tracking and task motivation is demonstrated in the previous research, which has shown that fitness tracking has a positive impact on consumers' motivation to be physically active (e.g., Butryn et al., 2016; Consolvo, Everitt, Smith, & Landay, 2006; Fritz, Huang, Murphy, & Zimmermann, 2014; Mauriello, Gubbels, & Froehlich, 2014; Preusse et al., 2017; Randriambelonoro et al., 2017). For example, Pettinico and Milne (2017) have found that fitness trackers increase users' anticipated motivation[10] for physical activity, while Attig and Franke (2018) have shown that motivation for physical activity decreases when fitness trackers are not available for users. Maitland et al. (2006) have also found that fitness tracking apps (with information sharing feature) lead to increased motivation for physical activities (e.g., walking). Notably, the majority of the previous studies have examined and confirmed the positive effects of fitness trackers on task motivation in goal-directed activities (e.g., specific activity goal is given) (e.g., Asimakopoulos, Asimakopoulos, & Spillers, 2017; Casey et al., 2014; Jarrahi et al., 2018), while limited research has investigated such effects when there is no specific goal given to the users. In real life, people may not always have a specific goal in mind while using fitness trackers (e.g., one may just want

[10] Anticipated motivation is defined as an individual's self-described expected level of motivation when presented with a program to achieve a goal (Pettinico & Milne, 2017).

to know his or her activity level). Therefore, it will be interesting to examine whether the identified relationship between fitness tracking and motivation will hold in such a situation.

4.2 Task/user experience

There has not been a consensus in the literature about the impacts of fitness tracking technologies on task/user experience. On the one hand, a number of studies has suggested a positive effect of fitness tracking on enjoyment (e.g., fun) in physical activities (e.g., Asimakopoulos et al., 2017; Canhoto & Arp, 2017; Mauriello et al., 2014). For example, Maitland et al. (2006) have shown that consumers find it fun to use fitness tracking apps (e.g., information sharing, competing), and they would enjoy an activity less if it is not being tracked (e.g., forget to wear the device) (Fritz et al., 2014). On the other hand, Etkin (2016) has found that fitness trackers (i.e., pedometer) reduce task enjoyment by making the task feel more work-like. Future research may further investigate such conflicting effects of fitness tracking on task/user experience.

4.3 Physical activity level

Previous research has confirmed the effectiveness of fitness tracking technologies in increasing consumers' physical activity levels (e.g., Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015; Consolvo et al., 2006; Etkin, 2016; Fritz et al., 2014; Maitland et al., 2006; Randriambelonoro et al., 2017). For example, using fitness trackers (e.g., Fitbit, pedometer) can increase the level of moderate-to-vigorous activities (Butryn et al., 2016; Jakicic et al., 2016; Pellegrini et al., 2012; Vallance, Courneya, Plotnikoff, Yasui, & Mackey, 2007) and goal directed activities (Croteau, Richeson, Farmer, & Jones, 2007; Glynn et al., 2014; Jarrahi et al., 2018; Kolt et al., 2012; Polzien, Jakicic, Tate, & Otto,

2007). Giddens, Leidner, and Gonzalez (2017) have also found that extended use[11] of a fitness tracker has a positive impact on physical activity level.

4.4 Well-being/health

Many researchers have investigated the effects of fitness tracking technologies on consumer well-being/health. Previous research has found that fitness trackers have a positive impact on consumers' perceived well-being (e.g., positive emotions, sense of accomplishment, or quality of life) and physical health (e.g., Asimakopoulos et al., 2017; Giddens et al., 2017; Randriambelonoro et al., 2017; Stiglbauer et al., 2019; Vallance et al., 2007). For example, the use of fitness trackers is an effective way to increase weight loss (Butryn et al., 2016; Fritz et al., 2014; Pellegrini et al., 2012; Polzien et al., 2007; Shuger et al., 2011) and reduce blood pressure (Kolt et al., 2012). However, Etkin (2016) has found a negative impact of fitness trackers on people's subjective well-being (e.g., happiness and satisfaction). Therefore, the effects of fitness tracking technologies on consumer well-being need further investigations.

4.5 Moderators for the relationships between fitness tracking and its outcomes

According to the previous research, the positive effects of fitness trackers on task motivation are stronger for an individual who has pre-existing motivation to be more active or who is under the age of 50 (Jarrahi et al., 2018; Pettinico & Milne, 2017). On the other hand, the positive impacts of fitness trackers on task motivation can be diminished in situations when, for example, people are too busy to exercise, poor at self-management, find exercise boring, have high fear of injury, and lack skills or support (e.g., encouragement or companionship) from family and friends and so on (Chang et al., 2016). In situations when fitness trackers are not available (e.g., forget to wear), motivation for physical activity deceases more for people with high extrinsic

[11] Extended use is defined as the number of features the user employs in addition to step counting (e.g., stair counting, workout tracking, goal setting, or social features) (Giddens et al., 2017).

motivation (e.g., to be fitter, to look good, or to lose weight), high need for cognitive closure (e.g., avoid ambiguous situations), and low hope of success (e.g., low approach tendency) (Attig & Franke, 2018).

Regarding the effects of fitness trackers on physical activity level, a stronger positive effect will occur when a fitness tracker is accompanied with Social Network Services (e.g., Facebook, Twitter) or with an individual's pre-existing motivation to be active (Chang et al., 2016; Jarrahi et al., 2018). In addition, to improve the activity level of currently inactive (or insufficiently active) older people, it is more effective to partner fitness trackers with individually matched motivational messages (e.g., communicating benefits of regular physical activity) than simply providing fitness trackers (Strath et al., 2011).

Moreover, there is a stronger positive effect of fitness tracker usage on perceived physical health and psychological well-being (e.g., positive emotion, experienced meaningfulness of life, and sense of accomplishment) when fitness trackers are accompanied with mobile applications (Stiglbauer et al., 2019).

4.6 Mediators for the relationships between fitness tracking and its outcomes

Previous research has found that fitness trackers can increase individuals' self-awareness (e.g., task progress, activity level, or value of activity), which in turn positively affects their task motivation (e.g., Casey et al., 2014; Fritz et al., 2014; Jarrahi et al., 2018; Mauriello et al., 2014; Preusse et al., 2017; Randriambelonoro et al., 2017). Fitness trackers can also increase task motivation by supporting users' self-efficacy (Casey et al., 2014; Fritz et al., 2014; Gualtieri et al., 2016) or basic psychological needs (i.e., autonomy, competence, and relatedness) (Asimakopoulos et al., 2017; Butryn et al., 2016). In addition, according to Pettinico and Milne (2017), the effect of a fitness tracker on anticipated task motivation is serially mediated by the perceived feedback meaningfulness (e.g., informative), the self-empowerment (e.g., higher sense of

personal control), and the goal focus. Casey et al. (2014) have also suggested that fitness trackers increase goal focus and sense of personal control over an activity.

In terms of task experience, Karapanos et al. (2016) have found that fitness tracking can positively influence users' pleasure by enhancing feelings of autonomy, competence and relatedness, whereas Etkin (2016) has shown that fitness tracker usage reduces task enjoyment by making the task feel more work-like. Future studies can explore under which conditions these two different processes occur.

5. Avenues for future research

Based on the current review, the authors suggest the following avenues for future research. First, previous studies have mainly used surveys and interviews for the investigation of the drivers of fitness tracking technology adoption, which may provide limited insight into the causal relationships between variables. Future research can employ other research methods (e.g., experiment) to directly test the causal links between fitness tracking technology adoption and its drivers (e.g., perceived benefits), and provide explanations for the corresponding causal mechanisms. It will also be interesting to investigate the relative importance or weight of each driver in determining fitness tracking technology adoption, along with the potential synergy effects of the different combinations of these drivers.

Second, a closer look at the literature on fitness tracking technology adoption reveals the lack of research investigating the antecedents of the drivers of fitness tracking technology adoption. For example, how marketers can increase consumers' perceived benefits (e.g., value, usefulness) of fitness tracking technologies, which can in turn influence consumer adoption of fitness tracking technologies? Previous research has shown that situational or contextual factors (e.g., need state, mood, product information, or product labeling) can influence consumers' value perceptions (e.g., Briers, Pandelaere, Dewitte, & Warlop, 2006; Chang & Wildt, 1994; Curren & Harich, 1994; Han, Chung, & Sohn, 2018). Future research endeavors thus can focus on

exploring situational factors (e.g., consumer emotion) that can lead to fitness tracking technology adoption by influencing its drivers that are identified in the current review.

Third, the extant research that has examined the effects of fitness tracking technologies on various consumer outcomes (e.g., motivation, experience, and well-being) has several methodological limitations. For example, few studies incorporated strict control conditions (e.g., no intervention) in their intervention designs, which can be directly compared to the treatment condition (e.g., use of a fitness tracker). The majority of previous studies also did not control for the potential confounding factors in their interventions, such as goal setting, social sharing, extra communication (e.g., messages, meetings, and counseling), or other features (e.g., game elements) implemented in the focal device (or app), which could have potentially driven the identified effect. Future studies thus can examine the relationships between fitness tracking and its outcomes by incorporating more strictly controlled experimental designs to provide further evidence to the downstream effect of fitness tracking. Investigation of the underlying process of the effect of fitness tracking can also contribute to the field. In addition, as previous research has been mostly conducted with specific population such as patients, seniors, or females, future research can examine the effect of fitness tracking on regular consumers and users.

Fourth, research that empirically examines the effects of fitness tracking technologies on task experience (e.g., enjoyment) is lacking, and the extant findings are inconclusive (e.g., positive vs. negative effect). Therefore, more research is needed to clarify the seemingly conflicting findings in the literature. It would also be interesting to examine the potential moderating effects of activity types (e.g., easy vs. difficult, physical vs. cognitive) or individual differences (e.g., gender, age, motivational orientation) on the relationship between fitness tracking and task experience. For example, Hsee, Yu, Zhang, and Zhang (2003) have argued that accumulation of a medium (e.g., points), especially when it requires effort, may produce a sense of accomplishment and competence, and thus generate task enjoyment. Therefore, fitness tracking feedback (e.g., distance ran, calories burned) may have a stronger positive impact on task

enjoyment when consumers are engaged in challenging (or effortful) activities (vs. effortless activities).

Lastly, the majority of previous research on fitness tracking has treated consumer motivation as a unilateral concept. Although this informs our understanding of the effect of fitness tracking on consumer motivation, further insights can be generated by considering the construct—motivation—as a multifaceted concept. For example, according to the self-determination theory, there are in general two types of motivation: intrinsic motivation[12] and extrinsic motivation[13] (Ryan & Deci, 2000b). In addition, extrinsic motivation can be further divided into four different categories: integrated motivation[14], identified motivation[15], introjected motivation[16], and external motivation[17] (Deci & Ryan, 2002). Previous research has shown that different types of motivation (e.g., extrinsic motivation vs. intrinsic motivation) can lead to different behavioral (e.g., low vs. high task persistence) and psychological outcomes (e.g., low vs. high well-being) (Ryan & Deci, 2000a). In addition, both extrinsic motivation and intrinsic motivation can be facilitated by external feedback based on the situational impact of the feedback on one's perceived autonomy, competence, and relatedness (Ryan & Deci, 2017). Therefore, it will be important to investigate how fitness tracking feedback affects the motivation of different types of consumers under different situations. Future

[12] Intrinsic motivation refers to doing an activity because it is inherently interesting or enjoyable (Ryan & Deci, 2000b).

[13] Extrinsic motivation refers to doing an activity in order to attain some separable outcomes (Ryan & Deci, 2000b).

[14] Integrated motivation refers to doing an activity because one has integrated the value of the activity with other aspects of his or her life (Ryan & Deci, 2000a).

[15] Identified motivation refers to doing an activity because one has identified the value of doing the activity (Ryan & Deci, 2000a).

[16] Introjected motivation refers to doing an activity in order to avoid guilt or anxiety or to attain pride (Ryan & Deci, 2000a).

[17] External motivation refers to doing an activity in order to satisfy external demand or obtain external reward (Ryan & Deci, 2000a).

research thus can contribute to the field by delving more deeply into the nature and dynamics of consumer motivation.

6. General discussion

As fitness tracking technologies emerge as a popular trend in various fields, the current study provides a timely review of the existing research on fitness tracking behavior. It contributes to the marketing discipline both by integrating a wide body of research on an important topic in consumer behavior and by offering an integrative agenda for future research. In particular, the current paper offers following contributions.

6.1 Theoretical contribution

First, the current paper identifies 18 drivers of fitness tracking technology adoption, which are then classified into four categories: user characteristics, device characteristics, perceived benefits/risks, and external drivers. Of the 18 drivers, 10 factors—age, technology affinity/self-efficacy, product involvement, device quality, device attractiveness/novelty, PEOU, PU, perceived enjoyment, perceived device value, and perceived (privacy) risk—are straightly aligned with the factors identified in the previous review on wearable technology adoption (Kalantari, 2017). Six factors—desire for feedback, current individual status, data quality, device functionality, financial incentives, and special situations—are newly discovered in the current review, and two factors—personality traits and social influences—are discussed with a focus on different aspects of the same constructs (vs. Kalantari, 2017). For example, the current paper identifies agreeableness and conscientiousness as important personality traits that drive fitness tracking technology adoption, whereas Kalantari (2017) has suggested openness to experience and neuroticism to be important drivers of wearable technology adoption. As for social influences, the current study recognizes social support and social connection, while Kalantari (2017) has identified subjective norms and social image. In addition, six factors (i.e., gender, visibility, physical risk, social risk, financial risk, and environmental risk) from the previous review (Kalantari, 2017) are not identified as influential factors in the current review. This suggests that there are differences

between the drivers of wearable technology adoption and the drivers of fitness tracking technology adoption, and fitness tracking technologies require an investigation on their own.

Second, the current paper reveals four main outcomes of fitness tracking: task motivation, task/user experience, physical activity level, and well-being/health. Specifically, previous research has found a positive effect of fitness tracking on outcome variables such as health, activity level, and motivation, whereas the effects of fitness tracking on task experience (e.g., enjoyment) and subjective well-being (e.g., feeling of satisfaction) have been inconclusive (e.g., positive vs. negative effect). Moreover, while the majority of previous research has focused on how fitness tracking technologies influence users' health, activity level, and motivation, the effect of fitness tracking on task/user experience has received little attention. Therefore, the authors encourage more research in this field to further examine the relationship between fitness tracking and task experience/subjective well-being.

6.2 Managerial implication

The current paper also delivers important practical implications. By providing an extensive overview of the drivers of fitness tracking technology adoption, this study can help designers and manufacturers of fitness tracking products to incorporate the features and functionalities (e.g., data quality, usefulness, and aesthetics) that are important for consumers, which would facilitate the adoption of their fitness tracking products. The increased knowledge of user characteristics will also help marketers employ more efficient segmentation strategies and marketing communications to better address the needs and concerns of consumers who are more likely to use or adopt their products. In addition, the current paper suggests that fitness tracking technologies are effective tools for consumers to improve their motivation, activity levels, and health. Marketers of fitness tracking technologies can thus appeal to their consumers by communicating the effectiveness of their products in providing such benefits. Overall, the findings from the current paper can act as a guide for marketers

to achieve a profitable business with fitness tracking products, which at the same time can benefit consumers both physically and psychologically.

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Paper 1: Appendix A. Summary of the papers that studied drivers of fitness tracking

			Drivers			
Study	Method	Sample (mean age)	User characteristics	Device characteristics	Perceived benefits/risks	External drivers
Attig and Franke (2018)	Survey	N = 210 Actual users, 92.4% F (24)	√			
Jarrahi et al. (2018)	Interview	N = 29 University staff, actual users, 65.5% F	√	√	√	
Rupp et al. (2018)	Survey	N = 103 Novice users, 53.4% F (36.5)	√		√	
Schall Jr et al. (2018)	Survey	N = 952 Engineers, 70.4% M (48.7)		√	√	
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)	√	√	√	√
Preusse et al. (2017)	Interview	N = 16 50% F (70)		√	√	
Randriambelonoro et al. (2017)	Interview	N = 18 Swiss patients, 61.1% F (36-73)		√	√	
Chang et al. (2016)	Interview Focus group	N = 15 Taiwanese Executive MBA students, 60% user, 73.3% M (median 45)	√	√	√	√
Coorevits and Coenen (2016)	Content analysis	N = 93 Comments on Reddit site		√	√	√
Epstein et al. (2016)	Survey & Interview	N = 193 56.5% M (31.6) & N = 12 66.7% F		√	√	√
Gualtieri et al. (2016)	Interview	N = 10 Patients, 80% F (61)			√	√
Karapanos et al. (2016)	Survey (MTurk)	N = 133 Actual users, 65% M (median 30)	√	√		
McMahon et al. (2016)	Interview	N = 95 Seniors, 75% F (79.8)			√	
Mercer et al. (2016)	Focus group	N = 32 Patients, 72% F (64)	√		√	
Rheingans et al. (2016)	Survey	N = 115 Germans, 53.9% F (25.9)			√	
Clawson et al. (2015)	Content analysis	N = 427 Posts on Craigslist site	√	√	√	√
Gao et al. (2015)	Survey	N = 462 Actual users, 53.7% F (32)	√	√	√	√
Harrison et al. (2015)	Survey Interview	N = 24 66.7% current users (vs. abandoned users), 54.2% F (18-55)	√	√		√
Lazar et al. (2015)	Interview	N = 17 Employees, 76.5% M (18-59)	√	√	√	
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)	√	√	√	√
Shin et al. (2015)	Focus group Interview	N = 15 Actual users	√			
Shih et al. (2015)	Survey	N = 26 Students, 69.2% M (20-24)		√		√
Choe et al. (2014)	Content analysis	N = 52 Video posts on Quantified-Self blog	√			
Kim (2014)	Survey Focus group	N = 18 Students, F (20-29)	√	√	√	√
Preusse et al. (2014)	Interview	N = 16 Seniors, 50% F (70)			√	
Whooley et al. (2014)	Content analysis	N = 51 Video posts on quantifiedself.com	√			
Gimpel et al. (2013)	Survey	N = 150 Actual users, 33% patients, 58% M (34)			√	√

Note: M refers to male, F refers to female. √ shows which drivers were tested in each study.

Paper 1: Appendix B. Summary of the papers that studied outcomes of fitness tracking

			Outcomes				Moderator	Mediator		
Study	Method	Sample (mean age)	Motivation	Experience	Physical activity	Well-being/health		Self-awareness	Psychological needs	Others
Stiglbauer et al. (2019)	Longitudinal experiment	N = 80 Students, 63% F (26.29)				√	√			
Attig and Franke (2018)	Survey	N = 210 Actual users, 92.4% F (24)	√				√			
Jarrahi et al. (2018)	Interview	N = 29 University staff, actual users, 65.5% F	√		√		√	√		
Asimakopoulos et al. (2017)	Survey	N = 34 Actual users, 61.8% M (18-60)	√	√		√			√	
Canhoto and Arp (2017)	Focus group	N = 20 German users, 55% M (25-32)		√						
Giddens et al. (2017)	Survey	N = 53 Bank employees, 79% F (18-75)			√	√				
Pettinico and Milne (2017)	Experiment (Scenario, MTurk)	N = 235 Non-users, 54% M (18-64)	√				√			√
Preusse et al. (2017)	Interview	N = 16 Seniors, 50% F (70)	√					√		
Randriambelonoro et al. (2017)	Interview	N = 18 Swiss patients, 61.1% F (36-73)	√		√	√		√		
Butryn et al. (2016)	Survey	N = 26 Community, F (54)	√		√	√			√	
Chang et al. (2016)	Interview Focus group	N = 15 Taiwanese Executive MBA students, 60% user, 73.3% M (median 45)	√				√			
Etkin (2016)	Experiment2 & Experiment 3	N = 95 Students, 67% F (21.1) & N = 100 Students, 67% F (20.7)		√	√	√				√
Gualtieri et al. (2016)	Interview	N = 10 Patients, 80% F (61)	√		√	√			√	
Jakicic et al. (2016)	Randomized weight loss intervention	470 Adults, 71.1% F (18-35)			√					

			Outcomes				Moderator	Mediator		
Study	Method	Sample (mean age)	Motivation	Experience	Physical activity	Well-being/health		Self-awareness	Psychological needs	Others
Karapanos et al. (2016)	Survey (MTurk)	N = 133 Actual users, 65% M (median 30)		√				√	√	
Mercer et al. (2016)	Focus group	N = 32 Patients, 72% F (64)	√					√		
Cadmus-Bertram et al. (2015)	Randomized self-monitoring intervention	N = 51 Overweight postmenopausal adults, F (60)			√					
Lazar et al. (2015)	Interview	N = 17 Employees, 76.5% M (18-59)			√			√		
Miyazaki et al. (2015)	Survey	N = 36 Active seniors, 58.3% F (68.3)			√	√				
Naslund, Aschbrenner, Barre, and Bartels (2015)	Interview	N = 10 Patients, 90% F (30-58)	√	√				√		
Randriambelonoro, Chen, Geissbuhler, and Pu (2015)	Interview	N = 18 Patients, 61.1% F (36-73)	√		√					
Seiler and Hüttermann (2015)	Survey	N = 206 Swiss students, 56% M (23)				√				
Shin et al. (2015)	Focus group Interview	N = 15 Actual users	√							
Shih et al. (2015)	Survey	N = 26 Students, 69.2% M (20-24)	√			√		√		
Casey et al. (2014)	Randomized controlled trial Interview	N = 12 Patients, 75% F (42)	√					√	√	√
Fritz et al. (2014)	Interview	N = 30 Actual users, 53.3% F (20-60)	√	√	√	√		√	√	
Glynn et al. (2014)	Randomized controlled trial	N = 90 Patients, 64% F (44.1)			√					
Mauriello et al. (2014)	Field study & Case study	N = 52 Running group members, 67.3% F (42) & N = 4 Running group members, 75% M (27.8)	√	√				√		

			Outcomes				Moderator	Mediator		
Study	Method	Sample (mean age)	Motivation	Experience	Physical activity	Well-being/health		Self-awareness	Psychological needs	Others
Thompson, Kuhle, Koepp, McCrady-Spitzer, and Levine (2014)	Randomized weight loss intervention	N = 48 Sedentary overweight patients, 81.2% F (79.5)			√	√				
Allen, Stephens, Dennison Himmelfarb, Stewart, and Hauck (2013)	Randomized weight loss intervention	N = 68 Obese patients, 78% F (45)			√	√				
Kolt et al. (2012)	Randomized controlled trial	N = 330 Low-active patients, 55.8% F (73.9)			√	√				
Pellegrini et al. (2012)	Randomized weight loss intervention	N = 51 Overweight patients, 86.3% F (44.2)			√	√				
Shuger et al. (2011)	Randomized weight loss intervention	N = 197 Sedentary obese adults, 81% F (46.8)				√				
Strath et al. (2011)	Randomized controlled trial	N = 61 Inactive seniors, 83% F (63.8)			√					
Jones, Richeson, Croteau, and Farmer (2009)	Focus group	N = 27 Seniors, 70.4% F (72.9)	√		√					
Croteau et al. (2007)	Randomized controlled trial	N = 147 Seniors, 78.2% F (72.9)			√					
Polzien et al. (2007)	Randomized weight loss intervention	N = 57 Sedentary people, 98.3% F (41.3)			√	√				
Vallance et al. (2007)	Randomized controlled trial	N = 377 Breast cancer survivors, (58)			√	√				
Aittasalo, Miilunpalo, Kukkonen-Harjula, and Pasanen (2006)	Randomized controlled trial	N = 265 Patients, 76% F (47)			√					
Consolvo et al. (2006)	Interview	N = 13 Friends, F (28-42)	√		√					
Maitland et al. (2006)	Interview	N = 9 Friends and co-workers, 55.6% F (19-54)	√	√	√					

Note: √ refers to tested; M refers to male, F refers to female. √ shows which outcomes, moderators and mediators were tested in each study.

Paper 2

Paper 2: Incidental curiosity and consumer intention to obtain unknown information: Implications for new product adoption and self-tracking behavior, under review at *Journal of Consumer Psychology*

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Abstract

This research examines how incidental curiosity influences consumers' intention to obtain curiosity-irrelevant unknown information. Previous studies have primarily focused on the effect of curiosity on consumers' desire to acquire curiosity-relevant unknown information (e.g., next episode of an interesting TV series). Would such incidentally induced curiosity influence consumers' response toward curiosity-irrelevant information? Three experiments demonstrate that curiosity can prompt consumers' intention to obtain curiosity-irrelevant unknown information (e.g., unknown product information, unknown self-related information). This occurs because curiosity can enhance consumers' perceived value of curiosity-relevant unknown information, and this positive perception of curiosity-relevant unknown information can spill over to curiosity-irrelevant unknown information. This research contributes to both curiosity and information avoidance literature and offers important practical implications for new product adoption and self-tracking behavior.

Keywords

Curiosity, new product adoption, perceived value, self-tracking, unknown information

1. Introduction

In daily life, consumers are often involved in curiosity inducing situations. For example, their curiosity can be activated by being exposed to an interesting movie trailer, a cliffhanger at the end of a TV series, or a gift in a wrapped box. In these situations, consumers will be keen to acquire information that can satiate their curiosity (e.g., next episode of the TV series)—curiosity-relevant unknown information. However, it is also common that consumers' curiosity is left unsatisfied because consumers simply cannot act upon their curiosity. Imagine that you are watching a TV series at home, and the episode ends with a cliffhanger. You feel curious and want to know what will happen next, but as the next episode will only be available next week, you have no choice but to wait. While you are still curious about the TV series, your friend shares an article with you regarding how to use a digital camera. The article has nothing to do with the TV series and is not curiosity stimulating in itself either, but it contains information that you don't know. Would incidentally induced curiosity (e.g., by a TV series) influence your response toward such curiosity-irrelevant unknown information (e.g., information about digital camera)?

Curiosity is a powerful motive that influences consumers' behavior (Steenkamp & Baumgartner, 1992). Previous research on curiosity has primarily focused on the impact of curiosity on consumers' desire to acquire curiosity-relevant unknown information (e.g., Althuizen, 2017; Hill, Fombelle, & Sirianni, 2016; Hsee & Ruan, 2016; Menon & Soman, 2002), while limited attention has been paid to the potential effect of curiosity on consumers' desire for curiosity-irrelevant unknown information. This research aims to examine this underexplored issue by investigating how curiosity influences consumers' intention to obtain curiosity-irrelevant unknown information.

Curiosity arises when one is deprived of curiosity-relevant unknown information (Wiggin, Reimann, & Jain, 2018). As deprivation can increase one's perceived value of the deprived object (e.g., money, food; Briers et al., 2006; Seibt, Häfner, & Deutsch, 2007), curiosity can enhance consumers' perceived value of curiosity-relevant unknown information. In addition, this positive perception of curiosity-relevant unknown

information can spill over to other information with the same attribute—unknown (e.g., curiosity-irrelevant unknown information), as perceptions can spillover among objects that have shared attributes or associations (e.g., similar brand or category; Du, Bhattacharya, & Sen, 2007; Janakiraman, Sismeiro, & Dutta, 2009; Votola & Unnava, 2006). Therefore, the authors propose that curiosity would increase consumers' intention to obtain curiosity-irrelevant unknown information (e.g., product-related or self-related unknown information) by increasing their perceived value of such information.

This research makes three important contributions. First, it adds to the curiosity literature by showing the effect of curiosity on consumers' perceptions of not only curiosity-relevant information but also curiosity-irrelevant information. Second, this research contributes to the literature on information avoidance by identifying curiosity as an important contextual factor that can overcome information avoidance by influencing consumers' desire for unknown information that is not curiosity stimulating (or interesting) in itself. Lastly, this research provides important practical insights into marketing strategies that can lead to more positive consumer response toward new (or unfamiliar) products (e.g., genetically modified food) and self-tracking products (e.g., activity tracking devices).

2. Theoretical background

2.1 Curiosity and perceived value of curiosity-relevant unknown information

Curiosity reflects an unsatisfied need state that arises when people identify or become aware of a lack of needed information to a specific unknown, such as the solution to a puzzle (Grossnickle, 2016; Isikman, MacInnis, Ülkümen, & Cavanaugh, 2016). Curiosity thus can be conceptualized as a cognitive deprivation that arises from the information gap (e.g., an incomplete story) between what one currently knows and what one desires to know (Loewenstein, 1994).

Previous research has shown that deprivation, defined as the condition of having lost or being prevented from having something essential (Ackerman & Gross, 2003), can influence consumers' perceptions of the deprived object (e.g., food; Seibt et al., 2007). This is because deprivation can create a need state, which can enhance the perceived value of need-related stimuli (Ferguson & Bargh, 2004). For example, the more active the need to eat (e.g., food deprivation), the more valuable the food will become (Brendl, Markman, & Messner, 2003). Value refers to perceived utility of an object in satisfying one's need (Salerno & Sevilla, 2019).

Similar to tangible objects (e.g., food, drink), deprivation of intangible objects (e.g., information) may also influence consumers' value perceptions. For example, although intangible, information has value in itself much like money or food (Marvin & Shohamy, 2016). Therefore, information deprivation can activate a need state—need for information, which can influence consumers' perceived value of the deprived information. This suggests that curiosity, by depriving curiosity-relevant unknown information (e.g., next episode of an interesting TV series), can increase consumers' perceived value of the curiosity-relevant unknown information.

2.2 Spillover effect on the perceived value of curiosity-irrelevant unknown information

Consumers evaluate an object based on diagnostic information available for the object (Aaker & Sengupta, 2000; Taylor & Bearden, 2002). Diagnosticity refers to the perceived relevance or usefulness of information in making a judgement (Ahluwalia, Unnava, & Burnkrant, 2001). If there is little diagnostic information about an object, consumers would rely on other information that can be perceived to be informative (diagnostic) about the focal object. Previous research has shown that consumers make inferences about an object on which information is not available (e.g., unknown) based on their perceptions of a similar or related object (Ahluwalia et al., 2001). This phenomenon is referred to as spillover effect, which occurs when existing perceptions influence beliefs that are not directly addressed by or related to the original perception object (Roehm & Tybout, 2006). For example, a negative message about a product's target attribute can

lead to negative perceptions of other attributes that are associated with the target attribute but not mentioned in the message (Ahluwalia et al., 2001). This is because the information (i.e., negative message) regarding the target attribute can be perceived as diagnostic of other attributes.

According to Janakiraman et al. (2009), whether information about an object will be viewed as diagnostic of other objects depends on whether the objects are associated in consumers' memory and how strong the associations are. Therefore, perceptions are more likely to spillover when the objects have shared attributes or associations (e.g., common brand name, common product category; Aggarwal & Shi, 2018). For example, consumers' perceptions of one product can influence their perceptions of another product in the same product category (Balachander & Ghose, 2003; Janakiraman et al., 2009) or in another product category but under the same brand family (Erdem & Sun, 2002; Pina, Riley, & Lomax, 2013). Therefore, if consumers have a positive (negative) experience with a product, they might form a positive (negative) inference (e.g., perceived quality) about other products, provided that these products have shared attributes or associations (Janakiraman et al., 2009).

The authors expect that perceptions can spillover across intangible objects (e.g., information) as well. That is, consumers' perceptions of specific information would influence their perceptions of other information that has shared attributes or associations. For example, if one values (or appreciates) real-time information about traffic condition because of a certain situational need (e.g., catch up a flight), this positive perception can spill over to other information that has the same attribute—real-time, such as real-time information about foreign exchange rate. Similarly, if curiosity can increase consumers' perceived value of curiosity-relevant unknown information (e.g., next episode of an interesting TV series), this positive perception of the specific unknown information can spill over to other curiosity-irrelevant information that has the same attribute—unknown (e.g., unknown product information). In this research, the authors define curiosity-irrelevant unknown information as information that is neither satiating an individual's stimulated curiosity nor curiosity stimulating in

itself but is unknown to the individual. The authors expect that when curious, consumers would have higher perceived value of curiosity-irrelevant unknown information.

2.3 Perceived value and intention to obtain curiosity-irrelevant unknown information

According to Overby and Lee (2006), value judgement can influence various consumer outcomes (e.g., preference, intention, and willingness to buy). Previous marketing studies have suggested a positive relationship between perceived value and behavioral intention. For example, consumers' perceived value of a product (e.g., service, food) has a positive effect on their purchase intention (Konuk, 2018; ST Wang, 2013). An interesting aspect of investigating the link between perceived value and consumer intention in this research is to see whether curiosity, by increasing perceived value of unknown information, can influence consumers' intention to obtain curiosity-irrelevant unknown information—a type of information that one would normally (e.g., if were not made curious) have little interest in obtaining.

In general, one may feel reluctant to obtain unknown information when the information is not curiosity stimulating or interesting in itself, as obtaining new information requires cognitive effort. This cognitive cost may become a barrier in forming consumer intention. For example, if one has little interest in cooking, he or she may have little desire to obtain unknown information about cooking. Curiosity, however, may help overcome such a barrier by increasing perceived value of unknown information. As a result, curiosity would prompt consumers' desire for curiosity-irrelevant unknown information, so that they would become more receptive to such information (e.g., unknown product information, unknown self-related information) available in the environment. This positive effect of curiosity on consumers' intention to obtain curiosity-irrelevant unknown information can be inferred from the study from Gruber, Gelman, and Ranganath (2014), which has shown that people can recall curiosity-irrelevant unknown information (e.g., faces of unfamiliar people) better during states of high curiosity (e.g., answering trivia questions) than states of low curiosity. Taken together, the authors hypothesize that:

H1. Increased curiosity results in the increased intention to obtain curiosity-irrelevant unknown information.

H2. The impact of curiosity on the intention to obtain curiosity-irrelevant unknown information is mediated by the perceived value of curiosity-relevant unknown information and subsequently the perceived value of curiosity-irrelevant unknown information.

3. Experiment 1

Experiment 1 tested Hypothesis 1 by examining the effect of curiosity on intention to read curiosity-irrelevant unknown information. The authors manipulated curiosity in three conditions (curious vs. incurious vs. neutral control), and then measured how much time participants allocated to read curiosity-irrelevant unknown (vs. familiar) information. The authors expected that curious (vs. incurious or neutral control) participants would allocate more time to read the curiosity-irrelevant unknown information.

3.1 Design and Method

One hundred twenty-eight participants (females = 71, males = 56, NA= 1) located in the USA were recruited through Amazon's Mechanical Turk (MTurk). The authors manipulated curiosity by using a reading task. Specifically, in both curious and incurious conditions, participants read short articles regarding three different questions (e.g., "What if everyone on Earth jumped at once?"). The only difference between the two conditions was that in the curious condition, the text was just describing each question without answering them, whereas in the incurious condition, the text was directly answering each question. In the neutral control condition, participants were shown the general driving rules in the USA with comparable length to the other two conditions (see Appendix A.1). Participants were only asked to read and evaluate the content of the column rather than solve any problems. After reading the column, participants were asked to evaluate the content of the column to maintain the cover story. Then, all participants were asked to indicate their curiosity level using two items adapted from

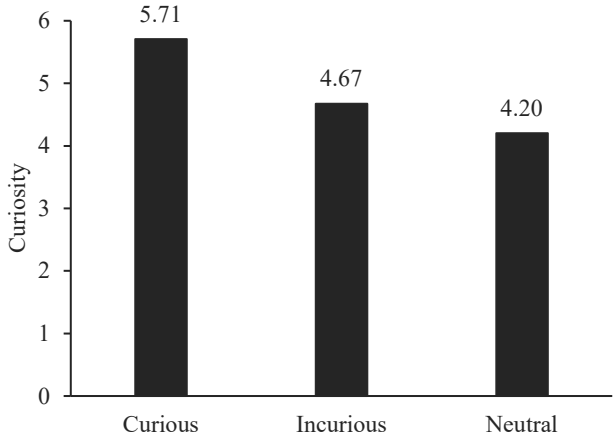
Wang and Huang (2017), on a seven-point scale (1 = not at all, 7 = very much; e.g., "How curious are you about the consequences of the questions in the column?" in the curious and incurious conditions; "How curious are you about the upcoming content of the column?" in the neutral control condition).

Next, participants completed a seemingly irrelevant second evaluation task for camera manuals (see Appendix B.1), in which the authors measured their intention to read curiosity-irrelevant unknown information. Specifically, participants were asked to imagine that they had 60 minutes of free time. They were presented with two digital camera manuals and were asked how they would allocate their time (i.e., 60 minutes) to read about each camera manual. One manual (i.e., manual I) contained familiar information (e.g., how to charge battery), and the other one (i.e., manual II) contained unknown information (e.g., how to adjust aperture). Participants freely allocated 60 minutes across the two manuals. Afterward, participants indicated how familiar they were about the content of each manual on a seven-point scale.[1]

3.2 Results

Curiosity manipulation. A one-way ANOVA on curiosity showed a significant main effect of treatment ($F(2, 125) = 11.54$, $p < .01$, $d = 1.02$). Participants in the curious condition ($M = 5.71$, SD = 1.16) were more curious than those in the incurious condition ($M = 4.67$, SD = 1.48; $t(125) = 3.22$, $p < .01$, $d = 0.77$) and neutral control condition ($M = 4.20$, SD = 1.69; $t(125) = 4.71$, $p < .01$, $d = 1.03$). There was no difference between the latter two conditions ($t(125) = 1.49$, $p = .14$).

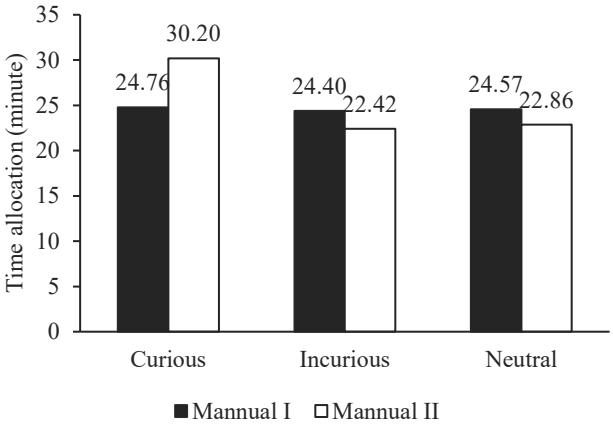
[1] In a pretest, 39 participants (51.3% female) on MTurk were presented with the camera manual with unknown information, and were asked to rate how curious they were about the unknown information in the manual on a seven-point scale (1 = not at all, 7 = very much). The results indicated that participants did not find such information particularly curious ($M = 4.24$, SD = 1.88).



Paper 2: Figure 1. Experiment 1. Curiosity level across three conditions.

Information familiarity (manual I vs. manual II). Participants were indeed more familiar with the information presented in manual I than in manual II (M_I = 4.38, SD = 1.78 vs. M_{II} = 3.16, SD = 1.58; $t(127) = 6.94$, $p < .01$). Thus, manual II (vs. manual I) contained more curiosity-irrelevant unknown information.

Time allocation (manual I vs. manual II). A one-way ANOVA on time allocation revealed a significant main effect for the manual II ($F(2, 125) = 4.37$, $p = .02$, $d = 0.54$). Specifically, curious participants (M = 30.20, SD = 14.00) allocated more time to read about the curiosity-irrelevant unknown information (i.e., manual II) than incurious participants (M = 22.42, SD = 14.49; $t(125) = 2.64$, $p < .01$, $d = 0.56$) and participants in the neutral control condition (M = 22.86, SD = 12.59; $t(125) = 2.50$, $p = .01$, $d = 0.57$). There was no difference between the latter two conditions ($t(125) = 0.15$, $p = .88$). By contrast, all participants allocated similar amount of time to read about the curiosity-irrelevant familiar information (i.e., manual I; $M_{curious}$ = 24.76, SD = 11.69; $M_{incurious}$ = 24.40, SD = 15.73; M_{neu} = 24.57, SD = 13.57; $F(2, 125) < 0.01$, $p = .99$). Moreover, conducting simple contrasts within each condition, the authors found that curious participants had a higher preference for the curiosity-irrelevant unknown (vs. familiar) information ($t(40) = 2.11$, $p = .04$, $d = 0.43$), whereas incurious participants ($t(42) = 0.63$, $p = .53$) and participants in the neutral control condition ($t(43) = 0.59$, $p = .56$) did not display such preference.



Paper 2: Figure 2. Experiment 1. Curiosity increased the time allocated to read curiosity-irrelevant unknown information (i.e., manual II) compared to curiosity-irrelevant familiar information (i.e., manual I).

3.3 Discussion

The results provided support for Hypothesis 1 by showing that curiosity prompted participants' intention to read curiosity-irrelevant unknown information. One may argue that curiosity manipulation might also generate need for closure (NFC) or feeling of uncertainty, which might lead to information-seeking behavior. However, this explanation is not likely for the following reasons. First, if NFC was activated by the curiosity manipulation, then participants should have chosen familiar information over unknown information. This is because NFC is a tendency to desire simple answers over complex ones (Litman, 2010), and people would engage less in the processing of new information under a heightened NFC (Kruglanski, Peri, & Zakai, 1991). Second, uncertainty motivates information seeking by generating negative emotions such as fear, anxiety, and worry (Tiedens & Linton, 2001; Wyer Jr, Dong, Huang, Huang, & Wan, 2019), and Wang and Huang (2017) has shown that curiosity does not induce such negative affect. It is also difficult to imagine that reading about such curiosity stimulating questions (see Appendix A.1) would meaningfully induce negative emotions. Thus, the authors conclude that the curiosity effect cannot be explained by NFC or feeling of uncertainty. In Experiment 2, the authors examined the underlying mechanism of the effect of curiosity on intention to obtain curiosity-irrelevant unknown information.

4. Experiment 2

Experiment 2 tested Hypothesis 2 by investigating the process through which curiosity increases consumers' intention to obtain curiosity-irrelevant unknown information. The authors manipulated curiosity (curious vs. incurious vs. neutral control), and then measured participants' likelihood of reading unknown (vs. familiar) product information. The authors expected that curiosity (vs. incuriosity or neutral control) would enhance the perceived value of curiosity-relevant unknown information, which in turn would increase the perceived value of curiosity-irrelevant unknown information, in this case, unknown product information. As a result, curiosity would prompt participants to read the information about an unknown product.

4.1 Design and Method

Two hundred twelve participants (females = 101, males = 109, NA= 2) located in the USA were recruited through MTurk. Curiosity was manipulated in a similar way to Experiment 1 by using three short news articles (see Appendix A.2). In the curious condition, participants read question type news (e.g., "Does Thinking Burn Calories?") with the content only describing the questions (i.e., not answering the questions), while in the incurious condition, participants read the same news but with the content directly answering the questions. In the neutral control condition, participants read statement type news (e.g., "Dietitian Says Eating Pistachios is Healthy.") with the content providing further details. After reading the news, curiosity level was measured using similar items to those in Experiment 1. Next, participants' perceived value of the curiosity-relevant unknown information was assessed using four items adapted from Yang et al. (2016; e.g., "Receiving information about the answers to the questions in the column is important to me"), on a seven-point scale (1 = not at all, 7 = very much). The items in the neutral control condition were slightly adjusted to better fit in their context (e.g., "Receiving information about the content of the news in the column is important to me.").

After the curiosity manipulation, participants were invited to another seemingly unrelated survey, in which they were asked to share their opinion on fruits and vegetables. Participants were presented with two identical pictures of tomatoes with different product labels: natural tomato versus transgenic (gene-modified) tomato (see Appendix B.2). The two labels were picked to make participants feel either familiar (natural tomato) or unknown (transgenic tomato) about the product. Afterward, participants answered some filler questions (e.g., "How often do you purchase natural/transgenic tomato?"), and indicated their likelihood of reading each product information (natural vs. transgenic tomato) on a seven-point scale. Then, participants' perceived value of the curiosity-irrelevant familiar/unknown information were measured using similar items to those used to measure their perceived value of curiosity-relevant unknown information (e.g., "Receiving product information about natural/transgenic tomato is important to me."), on a seven-point scale.[2]

4.2 Results

Curiosity manipulation. A one-way ANOVA on curiosity showed a significant main effect of treatment ($F(2, 209) = 12.89$, $p < .01$, $d = 0.82$). Participants in the curious condition ($M = 5.60$, SD = 1.33) were more curious than those in the incurious condition ($M = 4.66$, SD = 1.62; $t(209) = 3.70$, $p < .01$, $d = 0.63$) and neutral control condition ($M = 4.37$, SD = 1.54; $t(209) = 4.88$, $p < .01$, $d = 0.85$). There was no difference between the latter two conditions ($t(209) = 1.14$, $p = .25$).

Perceived value of curiosity-relevant unknown information. A one-way ANOVA on the perceived value of curiosity-relevant unknown information revealed a significant main

[2] In a pretest, 70 participants (58.6% female) on MTurk indicated their attitude toward the two types of tomatoes: natural tomato versus transgenic tomato. Participants were asked to rate them on four items using a seven-point scale (1 = not at all, 7 = very much): likability, familiarity, healthiness, and curiosity. The results indicated that participants perceived natural tomato (vs. transgenic tomato) as more likable ($M_{t\text{-}tomato} = 3.67$, SD = 1.92 vs. $M_{n\text{-}tomato} = 5.94$, SD = 1.54; $t(69) = 7.61$, $p < .01$), more familiar ($M_{t\text{-}tomato} = 2.91$, SD = 1.78 vs. $M_{n\text{-}tomato} = 5.93$, SD = 1.59; $t(69) = 9.89$, $p < .01$), and healthier ($M_{t\text{-}tomato} = 4.19$, SD = 1.84 vs. $M_{n\text{-}tomato} = 6.37$, SD = 1.21; $t(69) = 8.14$, $p < .01$). Participants were not more curious about transgenic tomato than natural tomato ($M_{t\text{-}tomato} = 4.63$, SD = 2.19 vs. $M_{n\text{-}tomato} = 4.44$, SD = 2.02; $t(69) = 0.61$, $p = .54$).

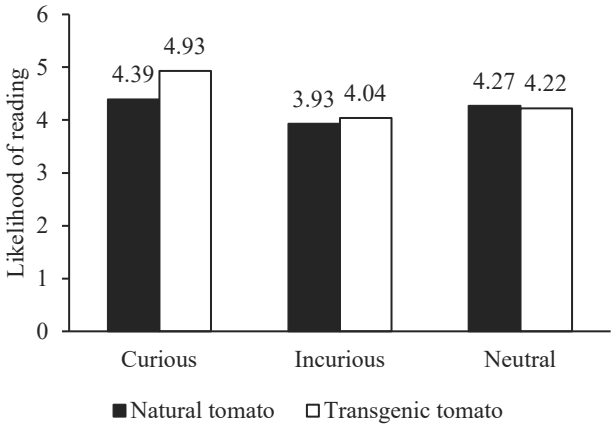
effect (F(2, 209) = 3.07, p = .05, d = 0.37). Specifically, participants in the curious condition (M = 5.03, SD = 1.34) had higher perceived value of the curiosity-relevant unknown information than those in the incurious condition (M = 4.55, SD = 1.43; t(209) = 2.08, p = .04, d = 0.35) and neutral control condition (M = 4.52, SD = 1.27; t(209) = 2.22, p = .03, d = 0.39). There was no difference between the latter two conditions (t(209) = 0.12, p = .91).

Perceived value of (curiosity-irrelevant) unknown product information. A one-way ANOVA on the perceived value of unknown product (i.e., transgenic tomato) information revealed a significant main effect (F(2, 209) = 3.19, p = .04, d = 0.37). As expected, participants in the curious condition (M = 4.74, SD = 1.65) had higher perceived value of the unknown product information than those in the incurious condition (M = 4.09, SD = 1.81; t(209) = 2.18, p = .03, d = 0.38) and neutral control condition (M = 4.08, SD = 1.83; t(209) = 2.21, p = .03, d = 0.38). There was no difference between the latter two conditions (t(209) = 0.01, p = .99).

Perceived value of (curiosity-irrelevant) familiar product information. There was no difference in the perceived value of familiar product (i.e., natural tomato) information across three conditions ($M_{curious}$ = 4.29, SD = 1.74; $M_{incurious}$ = 3.95, SD = 1.81; M_{neu}= 4.29, SD = 1.87; F(2, 209) = 0.86, p = .43). This suggested that the positive perception of curiosity-relevant unknown information did not spill over to the curiosity-irrelevant familiar information, as there was no shared attribute—unknown.

Likelihood of reading product information (unknown vs. familiar). A one-way ANOVA on the likelihood of reading product information revealed a significant main effect for the transgenic tomato (F(2, 209) = 4.10, p = .02, d = 0.37). Curious participants (M = 4.93, SD = 1.79) were more likely to read about the unknown product (i.e., transgenic tomato) information than incurious participants (M = 4.04, SD = 1.97; t(209) = 2.70, p = .01, d = 0.47) and participants in the neutral control condition (M = 4.22, SD = 2.02; t(209) = 2.19, p = .03, d = 0.37). There was no significant difference between the latter two conditions (t(209) = 0.55, p = .59). By contrast, all participants were equally likely to read about the familiar product (i.e., natural tomato) information ($M_{curious}$ = 4.39, SD = 2.19; $M_{incurious}$ =

3.93, SD = 2.12; M_{neu}= 4.27, SD = 2.07; $F(2, 209) = 0.89$, $p = .41$). Moreover, conducting simple contrasts within each condition, the authors found that curious participants had a higher preference for reading the unknown (vs. familiar) product information ($t(68) = 2.08$, $p = .04$, $d = 0.27$), whereas incurious participants ($t(69) = 0.40$, $p = .69$) and participants in the neutral control condition ($t(72) = 0.18$, $p = .86$) did not display such preference.



Paper 2: Figure 3. Experiment 2. Curiosity increased the likelihood of reading unknown product information (i.e., transgenic tomato) compared to familiar product information (i.e., natural tomato).

Mediation analysis. The authors used the SPSS macro PROCESS (model 6; Hayes, 2017) to test their serial mediation model. The results of path analysis (see Appendix C.1) showed that the impact of curiosity on the likelihood of reading unknown product information was serially mediated by the perceived value of curiosity-relevant unknown information and the perceived value of (curiosity-irrelevant) unknown product information. The 95% bias-corrected bootstrap confidence interval (using 10,000 bootstrap samples) did not include zero (0.024, 0.316). No other paths in the model revealed significant results.

4.3 Discussion

Experiment 2 provided support for Hypothesis 2 by showing that curiosity (vs. incuriosity or neutral control) increased participants' likelihood of reading unknown product information, and this effect was serially mediated by the perceived value of curiosity-relevant unknown information and the perceived value of (curiosity-irrelevant) unknown product information. Notably, product-related information is not the only type of information marketers provide to consumers. The recent technological development has given consumers the opportunity to obtain self-related information (e.g., step count, heart rate, and energy expenditure), for example, through self-tracking. Self-tracking refers to using modern technologies to monitor, track, and obtain personal information in real time. As self-tracking often allows consumers to obtain unknown self-related information (e.g., distance ran, heart rate), curiosity may prompt consumers' intention to use self-tracking products by increasing their perceived value of the (curiosity-irrelevant) unknown self-related information self-tracking products provide. The authors conducted Experiment 3 to test this assertion and, as a result, provided further support to Hypotheses 1 and 2 in a new context.

5. Experiment 3

Experiment 3 tested the effect of curiosity on intention to use self-tracking products by using a realistic product choice measure (i.e., self-tracking car adapter vs. non-tracking car adapter). The authors manipulated curiosity (curious vs. incurious vs. neutral control), and then measured participants' likelihood of purchasing self-tracking (vs. non-tracking) product. The authors expected that curious (vs. incurious or neutral control) participants would be more likely to purchase the self-tracking (vs. non-tracking) product.

5.1 Design and Method

One hundred ninety participants (females = 109, males = 80, NA = 1) located in the USA were recruited through MTurk. Curiosity was manipulated in the same way as in Experiment 2. Participants' curiosity level and the perceived value of curiosity-relevant unknown information were also measured using similar items to those in Experiment 2.

After the curiosity manipulation, participants were invited to another seemingly unrelated task, in which they were asked to evaluate a car gadget—fuel-saving car adapter. The authors provided two versions of the product (see Appendix B.3). The differences between the two product versions were that one version (i.e., self-tracking adapter) had the functionality to track driving information (e.g., duration, distance, and fuel consumed) and was priced higher ($40.30 vs. $32.20). The prices were chosen according to a pretest (N = 44, MTurk), which investigated participants' willingness to pay for each product version. Afterward, participants indicated their likelihood of purchasing each product version on a seven-point scale, given a budget of $45. Then, their perceived value of the curiosity-irrelevant unknown information (i.e., driving information) was measured using similar items to those in Experiment 2. Participants were also asked whether they thought the self-tracking adapter provided more unknown/new information about their driving than the non-tracking adapter, on a seven-point scale.[3] Later, the authors measured involvement with four items adapted from Wang and Huang (2017), on a seven-point scale.

5.2 Results

Curiosity manipulation. A one-way ANOVA on curiosity showed a significant main effect of treatment ($F(2, 187) = 7.55$, $p < .01$, $d = 0.69$). Participants in the curious condition ($M = 5.63$, SD = 1.44) were indeed more curious than those in the incurious condition ($M = 5.04$, SD = 1.38; $t(187) = 2.33$, $p = .02$, $d = 0.42$) and neutral control condition ($M = 4.66$, SD = 1.43; $t(187) = 3.86$, $p < .01$, $d = 0.70$). There was no difference between the latter two conditions ($t(187) = 1.52$, $p = .13$).

[3] In a pretest, 44 participants (56.8% female) on MTurk indicated their attitude toward the two product versions (self-tracking vs. non-tracking adapter). Participants were asked to rate them on two items (i.e., likable, indulgent) using a seven-point scale (1 = not at all, 7 = very much). The results indicated that participants perceived the two product versions as comparably likable ($M_{track} = 4.68$, SD = 1.71 vs. $M_{non\text{-}track} = 4.57$, SD = 1.37; $t(43) = 0.40$, $p = .69$) and indulgent ($M_{track} = 4.39$, SD = 1.76 vs. $M_{non\text{-}track} = 3.91$, SD = 1.71; $t(43) = 1.72$, $p = .09$). The authors also asked participants to rate how curious they were about their driving information on a seven-point scale. The results indicated that participants were not particularly curious about such information ($M = 4.27$, SD = 2.00).

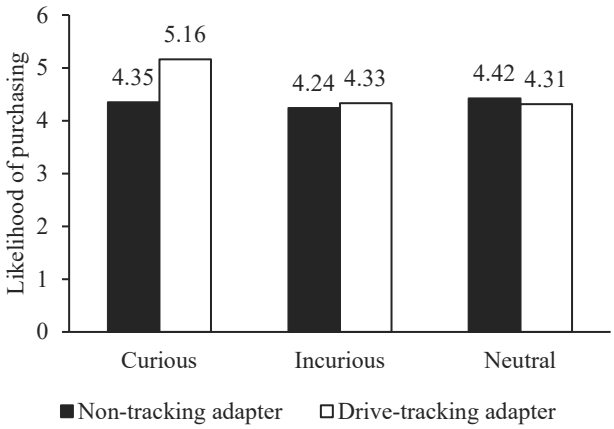
Perceived value of curiosity-relevant unknown information. A one-way ANOVA on the perceived value of curiosity-relevant unknown information revealed a significant main effect ($F(2, 187) = 3.70$, $p = .03$, $d = 0.39$). Participants in the curious condition ($M = 5.15$, SD = 1.33) perceived the curiosity-relevant unknown information as more valuable than participants in the incurious condition ($M = 4.54$, SD = 1.42; $t(187) = 2.50$, $p = .01$, $d = 0.44$) and neutral control condition ($M = 4.63$, SD = 1.36; $t(187) = 2.18$, $p = .03$, $d = 0.39$). There was no difference between the latter two conditions ($t(187) = 0.33$, $p = .74$).

Perceived information availability (self-tracking vs. non-tracking adapter). Compared to the non-tracking adapter, the self-tracking adapter was indeed perceived as providing more new information ($M = 5.86$, SD = 1.46) and unknown information ($M = 5.547$, SD = 1.67) about participants' driving.

Perceived value of (curiosity-irrelevant) unknown self-related information. A one-way ANOVA on the perceived value of unknown self-related information (i.e., driving information) revealed a significant main effect ($F(2, 187) = 5.31$, $p < .01$, $d = 0.42$). As expected, participants in the curious condition ($M = 5.13$, SD = 1.56) perceived the unknown self-related information as more valuable than participants in the incurious condition ($M = 4.26$, SD = 1.55; $t(187) = 3.12$, $p < .01$, $d = 0.56$) and neutral control condition ($M = 4.46$, SD = 1.63; $t(187) = 2.39$, $p = .02$, $d = 0.42$). There was no difference between the latter two conditions ($t(187) = 0.74$, $p = .46$).

Likelihood of purchasing car adapter (self-tracking vs. non-tracking). A one-way ANOVA on the likelihood of purchasing car adapter revealed a significant main effect for the self-tracking adapter ($F(2, 187) = 3.59$, $p = .03$, $d = 0.42$). Curious participants ($M = 5.16$, SD = 1.93) were more likely to purchase the self-tracking adapter than incurious participants ($M = 4.33$, SD = 2.04; $t(187) = 2.29$, $p = .02$, $d = 0.42$) and participants in the neutral control condition ($M = 4.31$, SD = 2.10; $t(187) = 2.36$, $p = .02$, $d = 0.42$) at a higher price ($40.3 vs. $32.2). There was no significant difference between the latter two conditions ($t(187) = 0.06$, $p = .95$). By contrast, all participants were equally likely to purchase the non-tracking adapter ($M_{curious} = 4.35$, SD = 1.76; $M_{incurious} = 4.24$, SD = 1.95; $M_{neu} = 4.42$, SD = 1.80; $F(2, 189) = 0.16$, $p = .85$). Moreover, conducting simple contrasts

from another perspective, the authors found that curious participants had a higher preference for the self-tracking (vs. non-tracking) adapter ($t(62) = 2.12$, $p = .04$, $d = 0.44$), whereas incurious participants ($t(62) = 0.26$, $p = .79$) and participants in the neutral control condition ($t(63) = 0.28$, $p = .78$) did not display such preference. In addition, curiosity did not affect involvement ($M_{curious} = 6.38$, SD = 0.84; $M_{incurious} = 6.08$, SD = 0.95; $M_{neu} = 6.24$, SD = 0.84; $F(2, 187) = 1.77$, $p = .17$), indicating that involvement could not explain the observed effect.



Paper 2: Figure 4. Experiment 3. Curiosity increased the likelihood of purchasing self-tracking product (i.e., drive-tracking adapter) compared to non-tracking adapter.

Mediation analysis. Consistently, a full conceptual model test indicated a significant indirect serial effect of the perceived value of curiosity-relevant unknown information and the perceived value of (curiosity-irrelevant) unknown self-related information on the relationship between curiosity and the likelihood of purchasing self-tracking adapter (see Appendix C.2). The 95% bias-corrected bootstrap (using 10,000 bootstrap samples) confidence interval did not include zero (0.046, 0.338).

5.3 Discussion

Experiment 3 extended the findings from Experiment 2 to the self-tracking domain. The authors found that curiosity (vs. incuriosity or neutral control) increased consumers' likelihood of purchasing the self-tracking adapter, and the effect was serially driven by

the perceived value of curiosity-relevant unknown information and the perceived value of (curiosity-irrelevant) unknown self-related information. This suggests that curiosity can increase consumers' perceived value of the unknown self-related information, which can drive their intention to use self-tracking products. In addition, from the analysis on the involvement measure, the authors can conclude that involvement did not explain the observed curiosity effect.

6. General discussion

This research investigates the effect of incidental curiosity on consumers' intention to obtain curiosity-irrelevant unknown information (e.g., unknown product information, unknown self-related information). A series of three experiments provides systematic support for both hypotheses. Experiment 1 documents the expected effect that curiosity prompts people to allocate more time to read curiosity-irrelevant unknown information. Experiment 2 provides direct process evidence that the perceived value of curiosity-relevant unknown information and the perceived value of curiosity-irrelevant unknown information serially mediate the positive effect of curiosity on the likelihood of reading curiosity-irrelevant unknown information. Experiment 3 extends the findings from Experiment 2 to the self-tracking domain by showing that curiosity increases the likelihood of purchasing self-tracking products.

6.1 Theoretical contributions

This research offers two main theoretical contributions. First, it adds to the curiosity literature. While previous research has shown that curiosity motivates consumers to seek curiosity-relevant unknown information (Kruger & Evans, 2009; Marvin & Shohamy, 2016; Menon & Soman, 2002; Van den Driessche et al., 2013; Van Dijk & Zeelenberg, 2007), this research shows that incidentally induced curiosity can also make consumers desire curiosity-irrelevant unknown information. This is because curiosity increases the perceived value of curiosity-irrelevant unknown information, and the authors offer process evidence for this mechanism. To the authors' knowledge, this research is the first to test the effect of curiosity on the perception of unknown

information, especially curiosity-irrelevant one. Second, this work contributes to the research on information avoidance. Consumers may avoid information when they lack time and energy to obtain it or when the information is, for example, not interesting, unfavorable, or threatening. While previous research has largely focused on the reasons why people avoid information (Golman, Hagmann, & Loewenstein, 2017; Sweeny, Melnyk, Miller, & Shepperd, 2010), little attention has been paid to the factors that can prevent such information avoidance. This research documents curiosity as an important contextual factor that can potentially overcome information avoidance by influencing consumers' desire for unknown information that is neither curiosity stimulating nor interesting in itself.

6.2 Managerial implications

This research also offers important practical implications for new product adoption and self-tracking behavior. First, the authors suggest useful strategies for marketers of innovative products. Innovative products often possess new benefits that may conflict with consumers' existing category expectations. According to Jhang, Grant, and Campbell (2012), when new products (e.g., Crystal Pepsi) are highly incongruent with consumers' expectations, it is difficult for consumers to understand their benefits. Consumers may also have low interest in exerting extra effort (e.g., searching unknown information) to learn about these products (e.g., genetically modified food, functional food). For example, gene modified foods may sound suspicious and weird, and thus consumers may not find them interesting or curious, which can be inferred from the pretest of Experiment 2 in this research (e.g., participants had a negative attitude toward gene modified tomatoes and were not curious in reading about them). Highly innovative products thus may fall through when marketers fail to inform consumers about the benefits of these products (Mesías Díaz, Martínez-Carrasco Pleite, Miguel Martínez Paz, & Gaspar García, 2012). Curiosity, as an external stimulus, may help marketers overcome this challenge by prompting consumers to acquire unknown information about the product (as being shown in Experiment 2), which can help consumers better understand the unknown product's benefits, and thus make them

more likely to adopt the product. Therefore, marketers might want to stimulate consumers' curiosity before the introduction of their new products or want to present their new products to consumers who are in a state of high curiosity. Inducing curiosity can be an effective way to make consumers obtain unknown information about highly innovative and, therefore, often incongruent products.

Second, this research offers valuable insights for existing challenges in consumer adoption of self-tracking technologies. According to Canhoto and Arp (2017), self-tracking technologies suffer from relatively low adoption rate. Therefore, identifying external factors that can increase consumers' intention to use such technologies would be of great importance for marketers of self-tracking products (e.g., wearables, apps). One of the reasons for some consumers not adopting or using self-tracking technologies could be due to their low interest in self-related information (e.g., step count, heart rate), and thus see no value of using or buying such technologies. Marketers of self-tracking products might be able to overcome such a challenge by evoking consumers' curiosity, as curiosity can increase consumers' perceived value of the unknown information that self-tracking products provide, and thus increase consumers' intention to use or purchase such products (as being shown in Experiment 3). One possible strategy could be to make consumers curious when they enter a store or to present self-tracking products to consumers who are in a curious state (e.g., show the advertisement right after a movie trailer).

6.3 Limitations and avenues for future research

It is important to note the limitations of this research, and suggest avenues for future investigations. First, all experiments in this research were conducted on the MTurk platform. Although the participants represent a wide range of age groups and vocations, care should be taken in generalizing results from one particular type of sample. Future research is needed to determine if the results from this research hold in other settings.

Second, as this research primarily focuses on the effect of curiosity on consumers' behavioral intention (e.g., intention to read) toward unknown information, it would be

beneficial to examine consumers' actual behaviors, such as whether curious (vs. incurious) consumers would read more about curiosity-irrelevant unknown information. Future research can also directly measure NFC and feeling of uncertainty to better address the potential alternative explanations.

Third, the authors take an initial step in examining how curiosity influences consumers' intention to obtain unknown information that is neither curiosity stimulating nor interesting in itself. Future work could investigate how curiosity would influence one's response toward potentially negative but beneficial unknown information (e.g., criticism). In addition, it would also be interesting to investigate how curiosity influences consumer experience of consuming unknown information. For example, would curiosity enhance enjoyment (or reduce boredom) of consuming (e.g., reading) curiosity-irrelevant unknown information by reducing perceived learning cost?

Fourth, in this research, the authors have focused on the situations when consumers have no time (or means) to act upon their curiosity. For example, after reading the curiosity stimulating material, participants were directly invited to the next session where the authors introduced a different task. In real life, there can be other situations when consumers would have some time to act upon their curiosity (e.g., search the Internet), which may potentially deplete their cognitive resource. Future research could investigate whether consumers would still show their desire for curiosity-irrelevant unknown information after they have exerted their cognitive effort to some extent.

Finally, as curiosity has been previously found to tempt indulgent choice by activating a desire for reward (Wiggin et al., 2018), it would be interesting to investigate how the perceived value of unknown information and the desire for reward together would predict consumers' behavior. For example, when given both the opportunity to obtain unknown information and the opportunity to indulge, such as having a choice of either reading a boring essay (e.g., learn new knowledge) or skipping it (e.g., indulge in laziness), would curious individuals resist the temptation of indulgence (e.g., skip the task) because of the enhanced perceived value of the unknown information that the

essay provides? The authors hope this research supports further examination of the issues mentioned above.

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Paper 2: Appendix A

Appendix A.1. Curiosity manipulation in Experiment 1

Curious condition (one question example):

What would happen if you shot a gun in space?

Guns do actually get carried to space, though not quite to the void between galaxies. The space guns are issued in case the cosmonauts need one back on Earth, so that they can protect themselves if emergency landing of their Soyuz spacecraft has left them deserted in a treacherous region. Fires can't burn in the oxygen-free vacuum of space, but guns can shoot. Modern ammunition contains its own oxidizer, a chemical that will trigger the explosion of gunpowder, and thus the firing of a bullet, wherever you are in the universe. No atmospheric oxygen required. The possibility of gunfire in space allows for all kinds of absurd scenarios. Here's where it gets interesting ... ... (writing in progress)

Incurious condition (one question example):

What would happen if you shot a gun in space?

Guns can shoot in space, and this allows for all kinds of absurd scenarios. Newton's third law dictates that the force exerted on the bullet will impart an equal and opposite force on the gun and, because you're holding the gun, you'll start moving backward. Thus, in the vacuum between galaxies, pulling the trigger will send you and your bullet careening through space literally forever. In space, theoretically you could shoot yourself in the back. You'd have to shoot horizontally at just the right altitude for the bullet to circle the planet and fall back to where it started (you). For example, if you shoot a gun toward the horizon while standing on a mountain on the moon, you could possibly shoot yourself in the back.

Neutral control condition:

General Driving Rules in the U.S.

General rules

- Vehicles drive on the right side of the road.
- Steering wheels are on the left side of the car.
- When making a left hand turn, pass in front of cars making similar left hand turns across the intersection.
- White lines are used to separate lanes of traffic moving in the same direction.
- Yellow lines are used to separate traffic headed in opposite directions.
  - Do NOT cross into lanes separated by lines that are solid yellow.
  - If the yellow line is broken, cross/pass with caution, but be highly aware of oncoming traffic.
- If you're behind a school bus with flashing red lights, you may NOT pass it until the lights have stopped flashing.
- Pedestrians always have the legal right of way.
  - If you see someone crossing the street, you must come to a full stop for them.
- Keep a careful eye out for motorcyclists and bicyclists.
  - In some states, bicyclists are required to ride in the street; while some cities have designated bike lines. Be aware of your surroundings.
- Car horns should be used sparingly and only if you fear someone putting you in danger.

For your safety

- Always wear your seatbelt.
  - If you have children, make sure that they're buckled in correctly before you begin to drive.
  - Children under a certain age or weight may be required to sit in a child safety seat or booster seat.
- Never drink and drive.
  - It is illegal in all states to drive while legally intoxicated.
- Don't text and drive.
  - In many states, texting and driving is illegal. Some prohibit the use of handheld devices for any reason, including for phone calls or navigation.
- Always use your turn signals.
  - Even if it seems like there's no one around you, always signal before you turn or make lane changes.
- On freeways and highways, slower traffic generally stays in the right-hand lanes, while faster drivers stick to the left-hand lanes.
- Hitchhiking is prohibited in most states, and can be very dangerous—do not attempt it, and do not pick anyone up.

... ... (writing in progress)

Appendix A.2. Curiosity manipulation in Experiments 2 and 3

Curious condition (one question example):

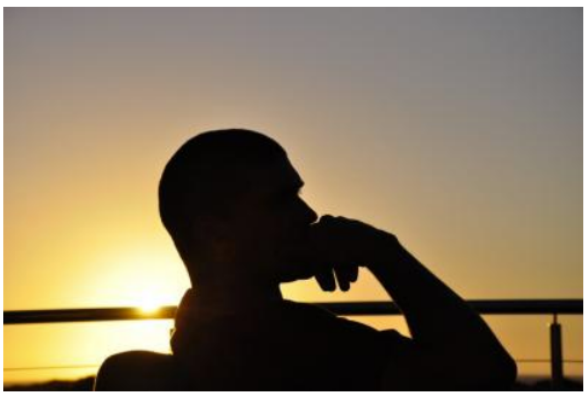
News 1

Does Thinking Burn Calories?

You spent Sunday on the couch, skimming your social feeds and watching a TV show. Monday at work was a different story; your job involves creative problem solving and other difficult mental activities. Does the extra brainpower you use at work burn more energy than your Sunday spent watching TV? Here's what the science says.

Incurious condition (one question example):

News 1



Does Thinking Burn Calories?

According to neuroscience, thinking hard indeed burns calories. This is because our brain runs on glucose, and the harder our brain works, the more glucose is burnt. However, while you may burn a few more calories thinking harder (vs. watching TV), it will barely affect your overall energy stores and not help you lose weight.

Neutral control condition:

News 1

Dietitian Says Eating Pistachios is Healthy

Pistachios are packed with vitamins, minerals and nutrients, which can help reduce the risk of chronic disease and improve heart health. Both raw and roasted pistachios contain a lot of fat, which is 17% of the recommended daily total. But most of the fat is a heart-healthy type that can help lower levels of bad cholesterol.

Paper 2: Appendix B

Appendix B.1. Dependent measure in Experiment 1

Compact digital camera manual I

- Exposure Triangle (aperture, shutter spped, ISO)
- Metering (average, center-weighted, spot metering)
- White balance (daylight, artificial light)

Compact digital camera manual II

- Preparation (battery, memory card)
- Shooting (focus, zoom, flash)
- Image view (browse, select, erase)

Please allocate your time across two manuals (60 minutes in total).

Minutes to read

0 10 20 30 40 50 60

Compact Digital Camera Manual I

Compact Digital Camera Manual II

Appendix B.2. Dependent measure in Experiment 2

Natural Tomato

Product information

Transgenic (gene modified) Tomato

Product information

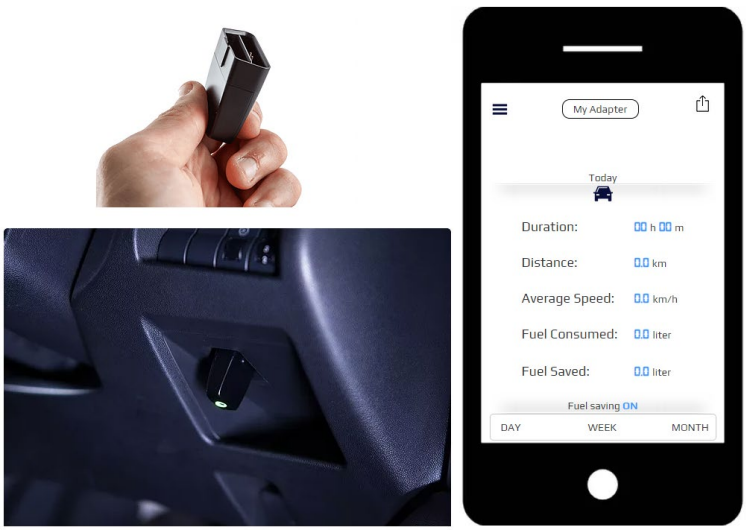
Appendix B.3. Dependent measure in Experiment 3

Self-tracking adapter:

Plugin Adapter A

Main feature:
- Fuel saving mode (reduce fuel consumption)
- Data tracking mode (track driving information)

Price:
- **40.30$**

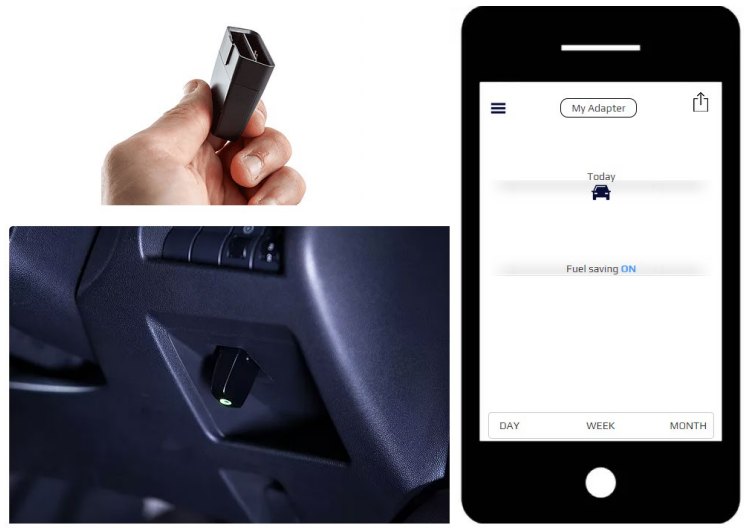


Non-tracking adapter:

Plugin Adapter B

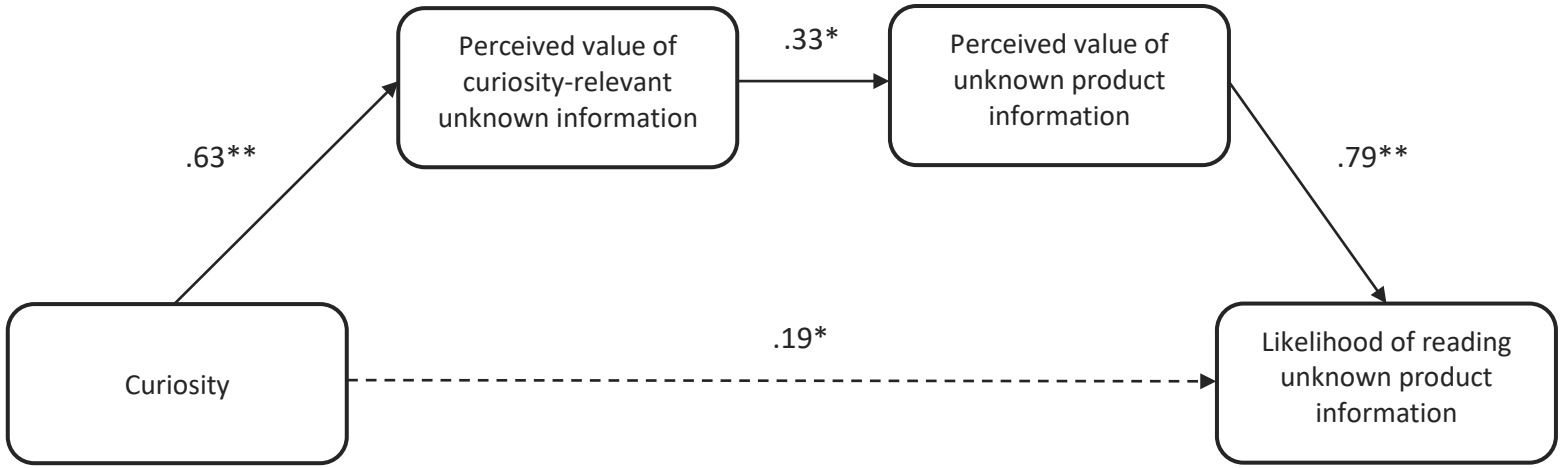
Main feature:
- Fuel saving mode (reduce fuel consumption)

Price:
- **32.20$**



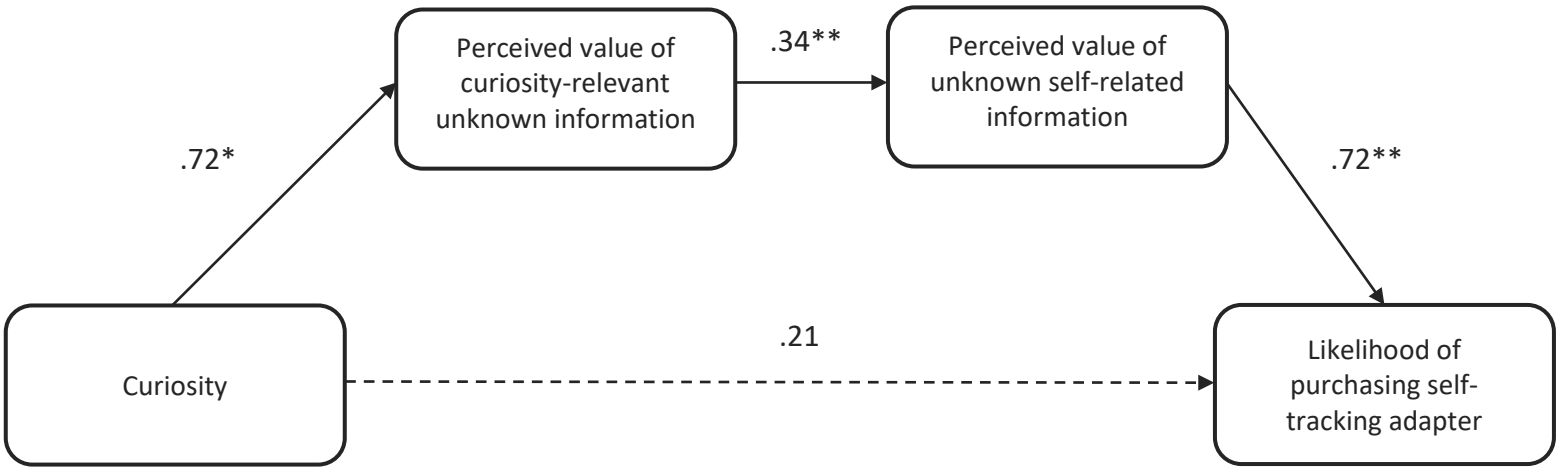
Paper 2: Appendix C

Appendix C.1. Serial mediation model path analysis (Experiment 2)



Note: *$p < .05$, **$p < .01$.

Appendix C.2. Serial mediation model path analysis (Experiment 3)



Note: *$p < .05$, **$p < .01$.

Paper 3

Paper 3: Self-tracking effortful tasks: gender differences in consumer experience, under review at *Journal of Consumer Behavior*

Jin. D., Halvari. H., Mæhle. N., Niemiec. C.P.

Abstract

Despite its growing popularity, the experiential side of self-tracking as a daily practice has received little attention in the literature. To cover this gap, the current research explores how self-tracking and gender influence consumer experience within effortful tasks. Three experiments demonstrate that for effortful tasks, self-tracking has contrasting effects on the task experience of different consumer segments: a positive effect on females, but a negative effect on males. This happens due to females' (vs. males') tendency to underestimate (vs. overestimate) themselves. As a result, self-tracking feedback helps females realize that they are more capable than they originally thought, and thus has a more positive impact on females' (vs. males') perceived competence, which leads to more positive task experience for females. However, this positive effect of self-tracking on females' task experience diminishes when females are made to overestimate themselves. This research contributes to both self-tracking and consumer experience literature and offers important practical implications.

Keywords

Consumer experience, gender, perceived competence, self-determination theory, self-tracking

1. Introduction

Self-tracking—using modern technologies to automatically track and collect personal information in numbers—has become a common practice in the lives of many consumers (Ajana, 2018), as increasing number of consumers embrace self-tracking technologies (e.g., activity trackers, apps) in their everyday activities. From relatively effortless activities (e.g., walking) to more challenging activities (e.g., running), consumers generate and obtain more information about their behavior than ever before (Etkin, 2016)—presenting a new opportunity for interactions that have the potential to benefit both consumers (e.g., self-knowledge) and marketers (e.g., consumer data).

Although self-tracking seems to be an appealing practice, recent research has suggested its hidden cost. That is, self-tracking relatively effortless tasks (e.g., coloring simple shapes) can reduce consumers' task enjoyment by making such tasks feel more work-like (Etkin, 2016). As positive consumer experience is critical in terms of consumer satisfaction (Dagger & O'Brien, 2010), loyalty (Ding & Tseng, 2015), and engagement (Grewal, Roggeveen, & Nordfält, 2017), such a negative impact of self-tracking on consumer experience may raise an important concern among marketers.

However, does self-tracking have a uniformly negative impact on consumer experience of other types (e.g., effortful) of tasks? Moreover, does self-tracking have a universal impact on different consumer segments (e.g., females vs. males)? It is well-established that external incentives (e.g., feedback, reward), although perceived as detrimental to enjoyment in general, can increase enjoyment in effortful tasks by increasing one's perceived competence (Deci, Koestner, & Ryan, 1999). Therefore, self-tracking as a feedback intervention can have a positive impact on consumer experience within effortful tasks by enhancing consumers' perceived competence. In addition, this positive impact would be stronger among females than males, as according to previous research (Buser, Geijtenbeek, & Plug, 2018; Henderlong Corpus & Lepper, 2007), females are more likely than males to underestimate their competence and see feedback as an opportunity to gain information about their competence. Hence, despite the

detrimental effect of self-tracking on enjoyment in effortless tasks, the current research proposes that consumers, especially females (vs. males), exhibit positive experience when self-tracking effortful tasks. The authors base their reasoning on the self-determination theory (SDT) and its mini-theory—cognitive evaluation theory (CET: Ryan & Deci, 2017)—to examine how self-tracking influences consumer experience (i.e., enjoyment, subjective vitality) within effortful tasks.

By identifying the effect of self-tracking on the task experience of different consumer segments, specifically in effortful tasks, the current research makes several important contributions. First, previous research on self-tracking has shown considerable interest in the consequences of self-tracking (e.g., activity output, health benefit, and anticipated motivation; Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015; Jakicic et al., 2016; Pettinico & Milne, 2017). However, little attention has been paid to the experiential side of self-tracking as a daily practice, and the existing research is limited to the impact of self-tracking within effortless tasks (e.g., walking, eating; Etkin, 2016; Weathers, Siemens, & Kopp, 2017). The current research therefore extends the self-tracking literature by investigating the effect of self-tracking on consumer experience within effortful tasks. In addition, the current research investigates the role of individual characteristics (e.g., gender) in relation to the effect of self-tracking on task experience. To the authors' knowledge, the current research is the first to test the role of gender in moderating the effect of self-tracking on task experience.

Second, there has been increasing interest in investigating various aspects of consumer experience in the marketing literature (Vom Lehn, 2006). A growing body of research points to the significant role of external stimuli in the constitution of positive consumer experience, such as ambient scent (Cirrincione, Estes, & Carù, 2014), atmospheric cues (Ha & Lennon, 2010), and gamification (Kim & Ahn, 2017). The current study adds to this line of research by identifying self-tracking as an external stimulus that can influence consumer experience of effortful tasks.

Lastly, positive consumer experience is important for companies to achieve a sustainable competitive advantage (Gentile, Spiller, & Noci, 2007). The current research

provides important strategical insights that can help firms (e.g., gyms, sports centers) improve consumer experience by using self-tracking technologies (e.g., activity trackers) or adding self-tracking features into their existing products (e.g., workout equipment). The findings of the current research can also help marketers identify consumer segments where self-tracking technologies can induce positive impacts on consumer experience.

2. Theoretical framework and hypotheses

2.1 Self-determination theory

Self-determination theory (SDT) is concerned with how social-contextual factors influence people's thriving through the satisfaction of their basic psychological needs for autonomy, competence, and relatedness (Ryan & Deci, 2017). In SDT, autonomy refers to the people's need for a sense of volition and feeling like they are the origin of their actions; competence describes the need for challenge and feelings of mastery; relatedness refers to the desire to feel socially connected and maintain meaningful relationships (Sørebø, Halvari, Gulli, & Kristiansen, 2009). According to SDT, satisfaction of these three needs can strongly affect people's psychological states, such as motivation, vitality, and well-being (Baard, Deci, & Ryan, 2004; Deci & Ryan, 2000).

Cognitive evaluation theory (CET) is a mini-theory developed within SDT that focuses exclusively on factors (e.g., perceived competence, perceived autonomy) that facilitate or undermine intrinsic motivation (e.g., enjoyment). In the current research, the authors will mainly focus on perceived competence, as self-tracking often offers reasonably high level of user autonomy (e.g., allows one to decide what to track and when to track it). According to CET, external feedback will affect people's task enjoyment to the extent that the feedback influences their perceived competence at a given task (Ryan & Deci, 2017). For example, feedback that promotes greater perceived competence can enhance task enjoyment by satisfying people's need for competence. Moreover, CET suggests that, through satisfaction of the competence need, external feedback can also be positively associated with another important aspect of task experience, namely

subjective vitality (Ryan & Deci, 2008). For example, there is a beneficial effect of feedback on the people's feelings of vitality and energy (Mouratidis, Vansteenkiste, Lens, & Sideridis, 2008). Self-tracking as a feedback intervention thus can positively influence consumer experience within effortful tasks by enhancing consumers' perceived competence.

2.2 Self-tracking and perceived competence within effortful tasks

Self-tracking refers to monitoring consumers' everyday lives to measure and quantify their activities (Whitson, 2013). By tracking how much of an activity one has done, self-tracking provides numerical feedback to consumers about their behavioral output (e.g., number of steps) (Etkin, 2016). This feedback is immediate, cumulative, and manifested in an increasing manner, and such cumulatively increasing numbers, provided as feedback, can give consumers a sense of competence and accomplishment (Earley, Northcraft, Lee, & Lituchy, 1990).

According to Shen and Hsee (2017), people respond positively to the increasing numbers that are linked to their behavior (e.g., word typing). Karapanos, Gouveia, Hassenzahl, and Forlizzi (2016) have also argued that numerical feedback can be rewarding, e.g., seeing health-related numbers stack up makes people feel healthier. This is because people have a tendency to focus on the immediate outcome over the more remote fundamental outcome, and thus are sensitive to the existence of a medium—a proxy representation of a more fundamental value (Hsee, Yu, Zhang, & Zhang, 2003). Similarly, self-tracking feedback can act as such a medium throughout a given task, which can facilitate positive outcomes. For instance, if one is running for the purpose of becoming healthy (fundamental value), the number of kilometers (medium) one has run can be perceived as a proxy representation of his or her healthiness. By looking at this number increasing, consumers will feel the adequacy of their behavior (running) in achieving their fundamental value—health. This will in turn boost their perceived competence in running.

However, such a positive impact of self-tracking on consumers' perceived competence can be more prominent within effortful (vs. effortless) tasks. Effortful tasks are associated with subjective difficulty and are mentally and/or physically demanding (Critchley, Corfield, Chandler, Mathias, & Dolan, 2000). Therefore, these challenges provide an environmental condition for stimulating one's need for competence (Jung, Schneider, & Valacich, 2010), and self-tracking feedback can satisfy this need. For instance, a college student would have higher desire to be competent at college math (effortful task) than at elementary school math (effortless task). Self-tracking feedback (e.g., number of problems solved) thus can be more meaningful and relevant when the college student is solving college math problems.

In addition, as an effortful accomplishment develops one's skills more fully, completing a task that demands high (vs. low) effort indicates more competence (Bandura, 1982; Jagacinski & Nicholls, 1987). Hsee et al. (2003) have also argued that the accumulation of a medium (e.g., points), especially when it requires effort, may produce a sense of accomplishment and competence, and thus generate task enjoyment. Continuing with the previous example of college students, for the majority of them, solving 20 elementary school math problems will be an effortless accomplishment, whereas solving 20 college math problems will be a more effortful accomplishment. In this case, self-tracking feedback can better indicate students' math competence in the latter condition. Therefore, self-tracking—by signaling one's accomplishment through numerical feedback—can positively influence consumers' perceived competence within effortful tasks.

2.3 The moderating role of gender

The authors further argue that the positive impact of self-tracking on consumers' perceived competence in effortful tasks is more likely to occur among females (vs. males). This is because there is a greater tendency for females to underestimate their competence (e.g., be modest or less self-confident), whereas males tend to overestimate theirs (e.g., overconfident) (Buser et al., 2018; Dasgupta, Mani, Sharma, &

Singhal, 2019; Herbert & Stipek, 2005; Pajares, 2002). As a result, existence of feedback can affect females and males differently (Roberts & Nolen-Hoeksema, 1989).

Past studies have demonstrated that females and males differ in their perceptions of the informational value of feedback. For example, females are more likely than males to perceive feedback to be informative about their competence (Roberts, 1991). Males in contrast, rely more on their own internal standards and tend to discount external feedback (Henderlong Corpus & Lepper, 2007). Therefore, self-tracking can affect females' (vs. males') perceived competence more positively in effortful tasks, as females can perceive self-tracking feedback as more informational. Without clear feedback, females' perceived competence in effortful tasks may suffer because of their tendency to underestimate themselves. Self-tracking feedback can help females realize that they are more capable than they originally thought, as sufficiently clear and verifiable information can eliminate self-evaluation bias (Jussim, Coleman, & Nassau, 1987).

Unlike females, males can perceive self-tracking feedback as less informational, as they are relatively independent of external feedback when judging their competence (Dweck, Davidson, Nelson, & Enna, 1978). In addition, as males tend to overestimate themselves, self-tracking feedback can make them realize that they are just as good as, if not worse than, they originally expected. Self-tracking feedback thus may have a weaker positive, if any at all, impact on males' perceived competence in effortful tasks.

H1. Self-tracking effortful tasks (relative to no self-tracking) leads to a higher increase in perceived competence among females than among males.

2.4 Task experience: enjoyment

Positive consumer experience is the key to unlocking new sources of competitive advantages (e.g., consumer preference) for firms (Frambach, Roest, & Krishnan, 2007). The current research thus investigates the downstream effect of self-tracking on the consumers' experience within effortful tasks. Although Etkin (2016) has found a negative effect of self-tracking on task enjoyment, the authors believe that the effect of self-tracking on task experience can differ within effortful tasks. The authors argue that

for effortful tasks, self-tracking can have a positive impact on consumers' task experience by enhancing their perceived competence at a given task. This is based on the notion that external incentives, although are often detrimental to enjoyment, can increase enjoyment within effortful tasks by increasing one's perceived competence (Deci et al., 1999).

According to Ryan, Mims, and Koestner (1983), external events such as reward and feedback can have two functional aspects: an informational aspect and a controlling aspect. Depending on the relative salience of these two aspects, external events can either enhance or reduce people's enjoyment. For example, the informational aspect of external events signifies people's competence at a given task and, as a result, enhances their task enjoyment, whereas the controlling aspect pressures people toward specified outcomes, and thus undermines their enjoyment (Promberger & Marteau, 2013; Ryan & Deci, 2000a). Therefore, self-tracking feedback can either enhance or reduce consumers' task experience depending on the salience of its informational or controlling aspect.

In Etkin's (2016) study, self-tracking effortless tasks could have facilitated the controlling aspect of self-tracking feedback, and thus reduced task enjoyment. As completing easy tasks does not indicate much of one's competence, self-tracking feedback can be less informational or meaningful for people within effortless tasks. On the other hand, completing an effortful task can indicate more of one's competence. Therefore, self-tracking feedback can have a more salient informational aspect than a controlling aspect when people are engaged in effortful tasks. As increased perceived competence will lead to higher task enjoyment (Ryan & Deci, 2000b), the authors propose that self-tracking can have a positive effect on consumers' enjoyment within effortful tasks by being more informative and indicative of one's perceived competence at a given task. This effect again, will be stronger for females (vs. males) because of the stronger positive impact of self-tracking on females' (vs. males') perceived competence.

H2a. Self-tracking effortful tasks (relative to no self-tracking) leads to a higher increase in enjoyment among females than among males.

H2b. For effortful tasks, gender moderates the indirect effect of self-tracking (relative to no self-tracking) on enjoyment through perceived competence such that the indirect effect is more positive among females than among males.

2.5 Task experience: subjective vitality

In addition, experience is more than just enjoyment (Kwan & Bryan, 2010), and it will be interesting to investigate how self-tracking influences other aspects of consumer experience—subjective vitality. Subjective vitality refers to the positive feelings of having energy available to the self (Chen & Sengupta, 2014). In general, engaging in effortful tasks can be depleting, as exerting effort on a cognitively (physically) demanding task consumes cognitive (physical) resources (Dragone, 2009). Effortful tasks thus can reduce one's subjective vitality. For instance, people will experience lower subjective vitality when physically or cognitively fatigued (Johnson, 2008; Ryan & Deci, 2017).

However, such a negative effect of effortful tasks on subjective vitality can be avoided when one's competence need is supported (Singh et al., 2005; Solberg, Hopkins, Ommundsen, & Halvari, 2012). Subjective vitality can be enhanced by activities that satisfy one's need for competence (Ryan & Deci, 2008). This notion is further supported by the studies showing that perceived competence is positively associated with subjective vitality even within highly effortful tasks (e.g., soccer, physical activity; Adie, Duda, & Ntoumanis, 2012; Taylor & Lonsdale, 2010). In a similar way, self-tracking can be positively associated with consumers' subjective vitality within effortful tasks by enhancing their perceived competence. More specifically, the authors propose that self-tracking can have a stronger positive impact on females' subjective vitality (vs. males') within effortful tasks, as self-tracking has a stronger positive impact on females' (vs. males') perceived competence.

H3a. Self-tracking effortful tasks (relative to no self-tracking) leads to a higher increase in subjective vitality among females than among males.

H3b. For effortful tasks, gender moderates the indirect effect of self-tracking (relative to no self-tracking) on subjective vitality through perceived competence such that the indirect effect is more positive among females than among males.

Moreover, if self-tracking influences females (vs. males) more positively because of their tendency to underestimate (vs. overestimate) themselves, as the authors suggest, then making females overestimate themselves to begin with should attenuate this positive effect. As a result, self-tracking should have weaker positive impacts on females' perceived competence and task experience within effortful tasks when they are overestimating themselves.

H4. Overestimation mitigates the positive impacts of self-tracking on females' perceived competence, enjoyment, and subjective vitality within effortful tasks.

3. Experiment 1

Experiment 1 examined how self-tracking affects consumers' (females' vs. males') perceived competence in an effortful task (Hypothesis 1). The authors predicted that self-tracking would have a stronger positive impact on females' (vs. males') perceived competence.

3.1 Design and Method

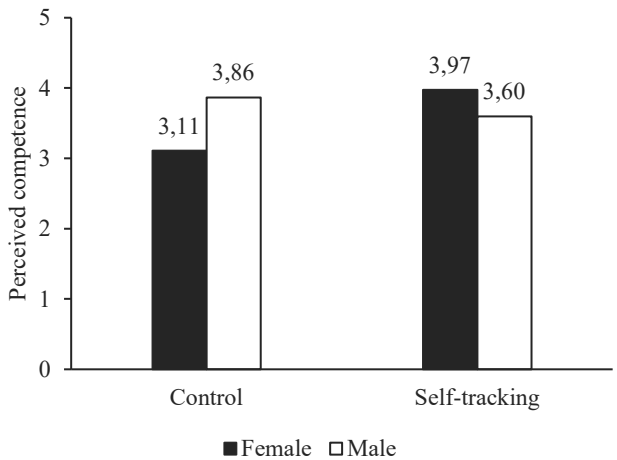
Two hundred twenty-two participants (females = 114, males = 108) located in the USA were recruited through Amazon's Mechanical Turk (MTurk). Participants were then randomly assigned to either the control or the self-tracking condition (see Appendix A). In both conditions, participants engaged in a riddle-solving task for 6 minutes. The only difference between the two conditions was the self-tracking feedback. In the self-tracking condition, participants were able to see their number of attempts and number of correct answers on the top right corner of the screen. In the control condition, no such numbers were visible, but an image icon of a comparable size was displayed on the same place. Participants were provided basic correct or incorrect feedback for each riddle in both conditions. After the riddle session, the authors measured participants'

perceived competence using four items adapted from Deci and Ryan (2003) on a seven-point scale (1 = strongly disagree, 7 = strongly agree). One sample items was "I think I am pretty good at riddles." Then the authors measured perceived task effortfulness using two items adapted from Jussim, Soffin, Brown, Ley, and Kohlhepp (1992; e.g., "I exerted a lot of effort in trying to solve these riddles in the riddle session.") on a five-point scale (1 = strongly disagree, 5 = strongly agree).

3.2 Results

Task effortfulness. As intended, participants exerted moderately high level of effort in the riddle-solving task in both conditions ($M_{control}$ = 3.67, SD = 0.92 vs. M_{track} = 3.60, SD = 0.98; $F(1, 220) = 0.36$, $p = .55$).

Perceived competence. A 2 (self-tracking) × 2 (gender) ANOVA on perceived competence revealed the predicted interaction effect ($F(1, 218) = 8.49$, $p < .01$ [one-tailed], $d = 0.77$). This was true even after controlling for the task performance ($F(1, 217) = 4.16$, $p = .02$ [one-tailed]), which was calculated as the score/attempt ratio. Self-tracking significantly increased females' perceived competence ($M_{control}$ = 3.11, SD = 1.29 vs. M_{track} = 3.97, SD = 1.63; $p < .01$ [one-tailed], $d = 0.59$), whereas did not affect males' perceived competence ($M_{control}$ = 3.86, SD = 1.45 vs. M_{track} = 3.60, SD = 1.40; $p = .32$; see Figure 1).



Paper 3: Figure 1. Experiment 1. Self-tracking increased perceived competence of females within an effortful riddle-solving task.

Alternative explanation. Previous research indicated that the congruence between gender and sex-type of a task can affect individuals' perceived competence (Vancouver, Ilgen, & Schmitt, 1989). For example, females would have higher perceived competence under feminine (vs. masculine) sex-typed tasks (Lirgg, Chase, George, & Ferguson, 1996). Thus, the identified gender difference in the current experiment could be due to such difference in females' perceived task sex-type across two experimental conditions. To test such an assumption, the authors had participants rate one question (i.e., "How would you rate riddle-solving task in terms of sex?") on a seven-point scale (1 = extremely feminine task, 7 = extremely masculine task). Further analysis revealed that there was no significant difference in perceived task sex-type among females across experimental conditions ($M_{control}$ = 4.05, SD = 0.78 vs. M_{track} = 3.84, SD = 0.99; p = .17). This ruled out the alternative explanation of gender and task sex-type congruence.

3.3 Discussion

Experiment 1 supported Hypothesis 1 by demonstrating that for effortful tasks, self-tracking can result in a higher increase in females' (vs. males') perceived competence. Perceived task sex-type did not account for this effect. The results provided initial evidence that task effortfulness can be an important contextual condition for stimulating consumers' need for competence, and self-tracking feedback can have a positive effect on their (e.g., females') perceived competence within effortful tasks.

Still, to provide further support for this assertion, the authors conducted a follow-up experiment on MTurk (N = 162) to examine the relationship between self-tracking and perceived competence within effortless tasks. The authors ran a version of Experiment 1, except that this time they made the task easier for the participants by providing answer hints (e.g., "What has hands but cannot clap? Hint: clo_k"). Results showed no significant interaction effect of self-tracking and gender on perceived competence (F(1, 158) = 2.33, p = .13). Females were not positively influenced by the self-tracking feedback when the task was effortless ($M_{control}$ = 5.33, SD = 1.19 vs. M_{track} = 4.88, SD = 1.20; p = .06, d = -0.38), neither were males influenced significantly ($M_{control}$ = 4.86, SD =

1.16 vs. M_{track} = 5.04, SD = 1.63; p = .51). The remaining experiments aimed to investigate the downstream consequences of self-tracking and its underlying mechanism.

4. Experiment 2

Experiment 2 had two objectives. First, it examined the effect of self-tracking on task enjoyment (Hypothesis 2a) and subjective vitality (Hypothesis 3a) within effortful tasks. Second, it tested the proposed underlying mechanism. The authors examined the mediated moderation hypothesis that gender moderates the indirect effect of self-tracking on enjoyment (Hypothesis 2b) and subjective vitality (Hypothesis 3b) through perceived competence.

4.1 Design and Method

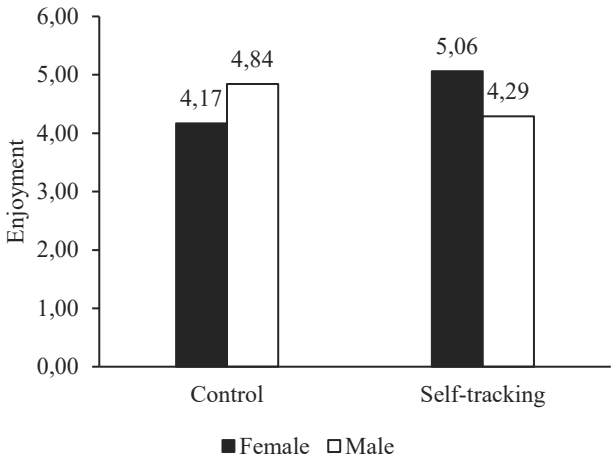
Two hundred twenty-six participants (females = 130, males = 96) located in the USA were recruited through MTurk. The authors manipulated self-tracking in the same way as in Experiment 1, but this time participants engaged in a math-solving task for 7 minutes (see Appendix B). After the math session, the authors measured enjoyment and subjective vitality using items (four items for each construct) adapted from Deci and Ryan (2003) on a seven-point scale (1 = strongly disagree, 7 = strongly agree). One sample item for each construct was "I enjoyed solving the riddles very much.", and "Now that I am finished with the riddle session, I feel alive and vital." Then participants rated their perceived task difficulty (i.e., "To what extent did you find the math problems challenging to solve?") on a seven-point scale (1 = not at all, 7 = completely) as the measure of task effortfulness. The authors also asked participants' previous experience with the task on a seven-point scale (i.e., "To what extent have you had experience with solving the math problems before participating in this experiment?").

4.2 Results

Task effortfulness. Participants perceived math-solving as a challenging (effortful) task in both conditions ($M_{control}$ = 5.21, SD = 1.08 vs. M_{track} = 4.98, SD = 1.31; F(1, 224) = 2.02, p = .16).

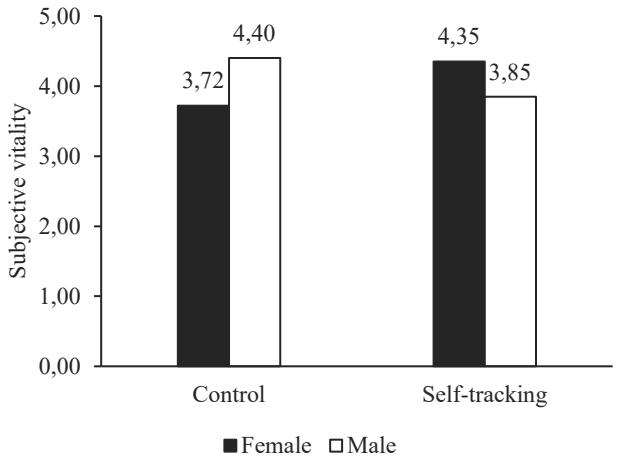
Perceived competence. A 2 (self-tracking) × 2 (gender) ANOVA revealed the predicted interaction effect (F(1, 222) = 4.18, p = .02 [one-tailed], d = 0.55). This was true with previous task experience being held constant (F(1, 221) = 4.24, p = .02 [one-tailed]). Self-tracking significantly increased females' perceived competence ($M_{control}$ = 3.89, SD = 1.58 vs. M_{track} = 4.56, SD = 1.31; p < .01 [one-tailed], d = 0.47), while did not influence males' perceived competence ($M_{control}$ = 4.41, SD = 1.29 vs. M_{track} = 4.29, SD = 1.56; p = .68).

Enjoyment. A 2 (self-tracking) × 2 (gender) ANOVA revealed the expected interaction effect (F(1, 222) = 12.80, p < .01 [one-tailed], d = 0.93). Self-tracking significantly increased females' enjoyment ($M_{control}$ = 4.17, SD = 1.74 vs. M_{track} = 5.06, SD = 1.31; p < .01 [one-tailed], d = 0.59), while marginally reduced males' enjoyment ($M_{control}$ = 4.84, SD = 1.33 vs. M_{track} = 4.29, SD = 1.64; p = .07, d = -0.37; see Figure 2).



Paper 3: Figure 2. Experiment 2. Self-tracking increased (vs. marginally reduced) enjoyment of females (vs. males) within an effortful math-solving task.

Subjective vitality. A 2 (self-tracking) × 2 (gender) ANOVA revealed a significant interaction effect (F(1, 222) = 10.46, p < .01 [one-tailed], d = 0.86). Self-tracking significantly increased females' subjective vitality ($M_{control}$ = 3.72, SD = 1.46 vs. M_{track} = 4.35, SD = 1.30; p < .01 [one-tailed], d = 0.46), while significantly reduced males' subjective vitality ($M_{control}$ = 4.40, SD = 1.25 vs. M_{track} = 3.85, SD = 1.39; p = .05, d = -0.42; see Figure 3).



Paper 3: Figure 3. Experiment 2. Self-tracking increased (vs. reduced) subjective vitality of females (vs. males) within an effortful math-solving task.

Underlying process. To test the full conceptual model, the authors ran a bias-corrected mediated moderation analysis (Hayes, 2013). As predicted, with self-tracking as the independent variable, gender as the moderator, perceived competence as the mediator, and enjoyment as the dependent variable, the 95% bias-corrected bootstrap confidence interval (CI), which the authors obtained using 10,000 bootstrap samples, did not include zero (-0.9006, -0.0286). The same result was revealed with subjective vitality as the dependent variable (bootstrap 95% CI [-0.6395, -0.0224]).

4.3 Discussion

The results from Experiment 2 provided support for Hypotheses 1, 2a, and 3a by demonstrating that self-tracking had stronger positive impacts on females' (vs, males') perceived competence, enjoyment, and subjective vitality within a real-world effortful task. The results also illustrated the causal mechanism of the downstream consequences of self-tracking. Specifically, gender moderated the indirect effect of self-tracking on task experience through perceived competence (Hypotheses 2b and 3b). As a result, self-tracking increased females' enjoyment and subjective vitality within an effortful task, whereas tended to decrease males' enjoyment and subjective vitality.

Notably, given no significant difference in the actual task performance ($F < 1$), females (vs. males) had lower performance expectancy (e.g., number of math problems one can solve correctly) prior to the task (M_{female} = 6.54, SD = 3.23 vs. M_{male} = 8.66, SD = 6.66; $F(1, 224) = 9.99$, $p < .01$). This result provided evidence for females' (vs. males') higher tendency to underestimate (vs. overestimate) themselves. Such a difference might have made females (vs. males) perceive self-tracking feedback as more informational (vs. controlling), and in turn led to their positive (vs. negative) task experience. In Experiment 3, the authors manipulated self-estimation to provide evidence for this assertion.

5. Experiment 3

Experiment 3 aimed to test Hypothesis 4 that if self-tracking influences females (vs. males) more positively because females underestimate (vs. overestimate) themselves, then making females overestimate themselves to begin with should attenuate this positive effect of self-tracking on females.

5.1 Design and Method

Three hundred twenty-seven participants (females = 205, males = 122) located in the USA were recruited through MTurk. Participants were explained that the authors were developing an app for word scramble quiz, and the authors wanted to test if the app functioned properly. Before moving to the main test session, participants were first invited to get familiar with the quiz for 3 minutes. The authors then provided performance feedback to manipulate participants' self-estimation. In the overestimation condition, participants received positive performance feedback at the end of the practice session (i.e., "You have performed better than 90% of our participants."), whereas those in the normal condition (control) did not receive such feedback.

The authors then measured participants' expectation of their own performance in the main session (i.e., number of quizzes one expects to solve correctly) as the manipulation check for overestimation. Participants in the overestimation condition should have

higher performance expectancy than those in the normal condition. The authors expected that this manipulation would make participants, especially females, overestimate themselves. Afterwards, participants were invited to the main session where they engaged in the same focal quiz for 7 minutes. Self-tracking was manipulated only in the main session and was manipulated in the same way as previous experiments (see Appendix C). The rest of the experiment followed the same procedure as previous experiments.

5.2 Results

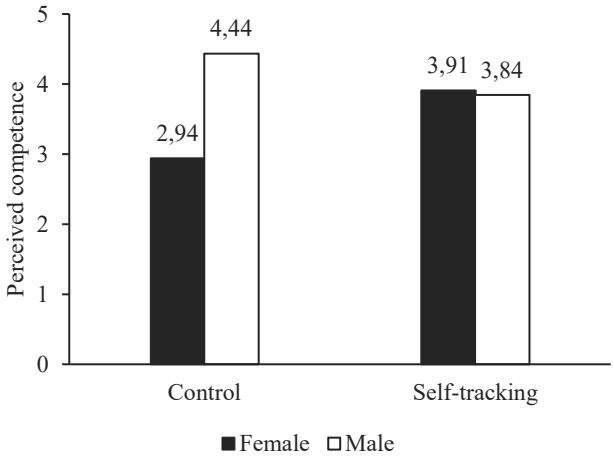
Performance expectancy. The manipulation check confirmed the effectiveness of the overestimation manipulation. Participants in the overestimation condition showed significantly higher performance expectancy than those in the normal condition (M_{normal} = 8.71, SD = 7.11 vs. $M_{overest}$ = 10.60, SD = 9.99; F(1, 325) = 3.85, p = .05, d = 0.22). Specifically, the manipulation was more effective on females (M_{normal} = 7.69, SD = 7.28 vs. $M_{overest}$ = 10.45, SD = 10.37; p = .03, d = 0.31) than on males (M_{normal} = 10.47, SD = 6.52 vs. $M_{overest}$ = 10.84, SD = 9.40; p = .70). This result was not surprising because males already possess the tendency to overestimate themselves (i.e., higher performance expectancy than females in the normal condition: M_{female} = 7.69, SD = 7.28 vs. M_{male} = 10.47, SD = 6.52; p = .02, d = 0.40). As a result, the effectiveness of the manipulation could have been mitigated for males.

Task effortfulness. Participants perceived word scramble quiz as an effortful task across normal and overestimation conditions (M_{normal} = 5.40, SD = 1.25 vs. $M_{overest}$ = 5.56, SD = 1.11; F(1, 325) = 1.56, p = .21).

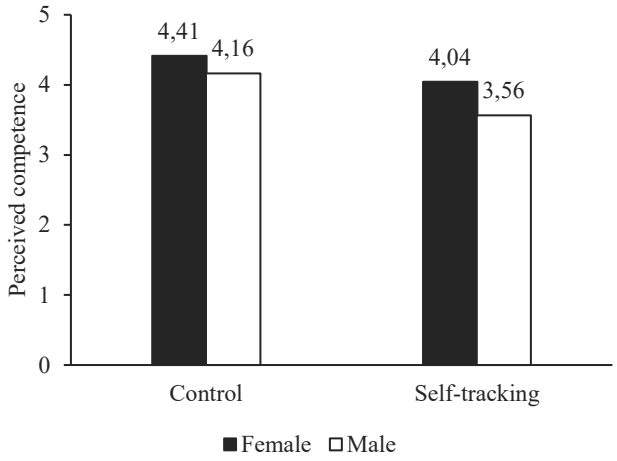
Three-way interaction. A 2 (self-tracking) × 2 (gender) × 2 (overestimation) ANOVA revealed significant three-way interaction effects on perceived competence (F(1, 319) = 2.78, p = .05 [one-tailed]), enjoyment (F(1, 319) = 3.00, p = .04 [one-tailed]), and subjective vitality (F(1, 319) = 3.63, p = .03 [one-tailed]).

Perceived competence. The result revealed a significant interaction effect of self-tracking and gender on perceived competence in the normal condition (F(1, 154) = 6.92,

$p < .01$ [one-tailed], $d = 0.84$) but not in the overestimation condition ($F(1, 165) = 0.19$, $p = .34$ [one-tailed]). Consistent with the previous experiments, in the normal condition, self-tracking significantly increased females' perceived competence ($M_{control} = 2.94$, SD = 1.73 vs. $M_{track} = 3.91$, SD = 1.78; $p < .01$ [one-tailed], $d = 0.55$), while did not significantly influence males' perceived competence ($M_{control} = 4.44$, SD = 1.81 vs. $M_{track} = 3.84$, SD = 1.92; $p = .17$; see Figure 4). In the overestimation condition, however, this positive effect of self-tracking on females was attenuated ($M_{control} = 4.41$, SD = 1.67 vs. $M_{track} = 4.04$, SD = 1.71; $p = .13$ [one-tailed]; see Figure 5). Males were still not affected significantly ($M_{control} = 4.16$, SD = 1.69 vs. $M_{track} = 3.56$, SD = 1.68; $p = .13$).

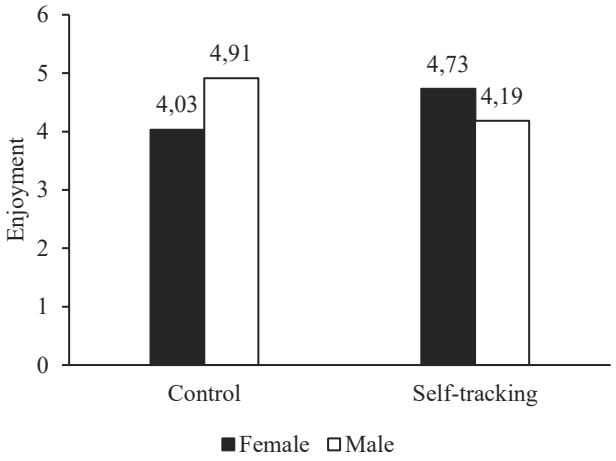


Paper 3: Figure 4. Experiment 3. In the normal condition, self-tracking increased perceived competence of females within an effortful quiz-solving task.

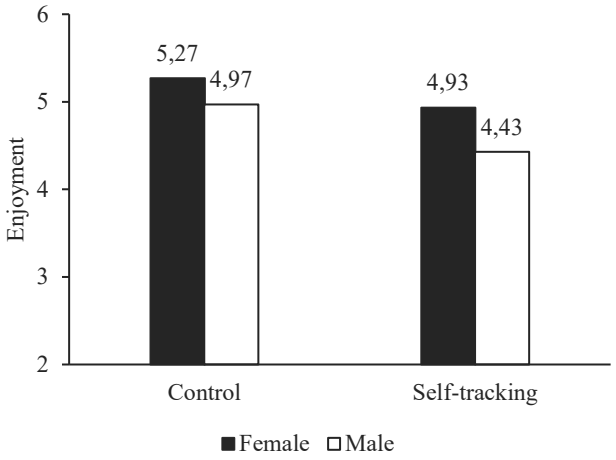


Paper 3: Figure 5. Experiment 3. In the overestimation condition, self-tracking did not increase perceived competence of females within an effortful quiz-solving task.

Enjoyment. A 2 (self-tracking) × 2 (gender) ANOVA revealed the significant interaction effect in the normal condition ($F(1, 154) = 6.80$, $p < .01$ [one-tailed], $d = 0.84$) but not in the overestimation condition ($F(1, 165) = 0.20$, $p = .33$ [one-tailed]). In the normal condition, self-tracking significantly increased females' enjoyment ($M_{control} = 4.03$, SD = 1.76 vs. $M_{track} = 4.73$, SD = 1.55; $p = .02$ [one-tailed], $d = 0.42$), while marginally reduced males' enjoyment ($M_{control} = 4.91$, SD = 1.47 vs. $M_{track} = 4.19$, SD = 1.86; $p = .09$, $d = -0.43$; see Figure 6). In the overestimation condition, again the positive effect of self-tracking on females was attenuated ($M_{control} = 5.27$, SD = 1.31 vs. $M_{track} = 4.93$, SD = 1.56; $p = .15$ [one-tailed]; see Figure 7). For males, although not significant, self-tracking consistently tended to decrease their enjoyment ($M_{control} = 4.97$, SD = 1.35 vs. $M_{track} = 4.43$, SD = 1.44; $p = .11$).



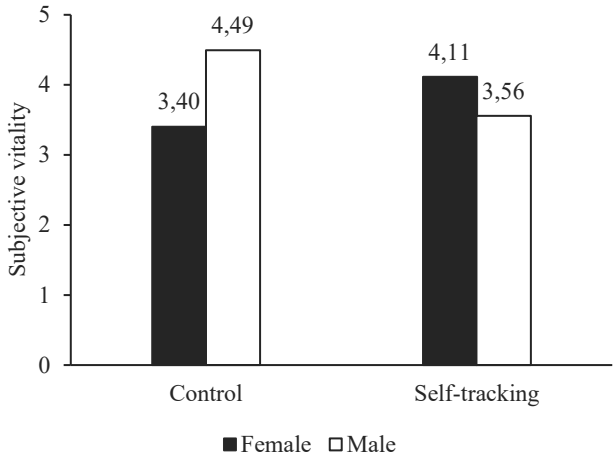
Paper 3: Figure 6. Experiment 3. In the normal condition, self-tracking increased (vs. marginally reduced) enjoyment of females (vs. males) within an effortful quiz-solving task.



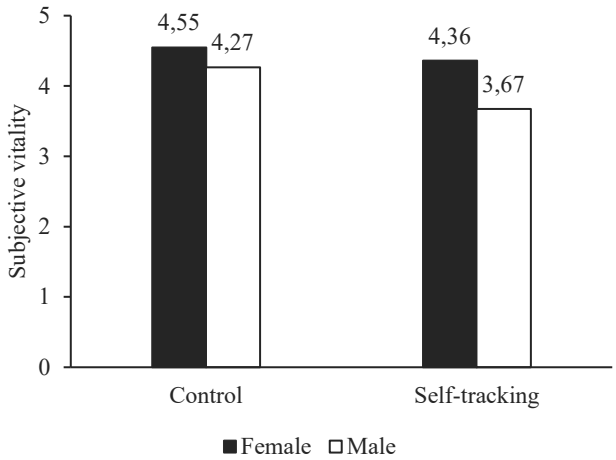
Paper 3: Figure 7. Experiment 3. In the overestimation condition, self-tracking did not increase enjoyment of females within an effortful quiz-solving task.

Subjective vitality. A 2 (self-tracking) × 2 (gender) ANOVA revealed a significant interaction effect in the normal condition ($F(1, 154) = 10.96$, $p < .01$ [one-tailed], $d = 1.05$) but not in the overestimation condition ($F(1, 165) = 0.91$, $p = .17$ [one-tailed]). In the normal condition, self-tracking significantly increased females' subjective vitality ($M_{control} = 3.40$, SD = 1.60 vs. $M_{track} = 4.11$, SD = 1.44; $p = .01$ [one-tailed], $d = 0.47$), while significantly reduced males' subjective vitality ($M_{control} = 4.49$, SD = 1.42 vs. $M_{track} = 3.56$,

SD = 1.56; p = .02, d = -0.63; see Figure 8). In the overestimation condition, as predicted, the positive effect of self-tracking on females was attenuated ($M_{control}$ = 4.55, SD = 1.31 vs. M_{track} = 4.36, SD = 1.40; p = .27 [one-tailed]; see Figure 9). Males' subjective vitality was consistently negatively influenced by the self-tracking ($M_{control}$ = 4.27, SD = 1.13 vs. M_{track} = 3.67, SD = 1.47; p = .05, d = -0.46).



Paper 3: Figure 8. Experiment 3. In the normal condition, self-tracking increased (vs. reduced) subjective vitality of females (vs. males) within an effortful quiz-solving task.



Paper 3: Figure 9. Experiment 3. In the overestimation condition, self-tracking did not increase subjective vitality of females and reduced subjective vitality of males within an effortful quiz-solving task.

5.3 Discussion

Experiment 3 supported Hypothesis 4 and provided further evidence for the underlying process of the gender effect by directly manipulating self-estimation. In the normal condition where females (vs. males) tended to underestimate (vs. overestimate) themselves, self-tracking had positive impacts on females' perceived competence and task experience within an effortful task. However, making females overestimate themselves attenuated such positive impacts. In this case, self-tracking no longer generated positive impacts on females' perceived competence, task enjoyment, and subjective vitality. These results provided direct evidence for the role of gender differences in self-estimation in shaping the effect of self-tracking on task experience within effortful tasks.

6. General discussion

Despite the growing use of self-tracking technologies among consumers, little empirical work has examined how self-tracking affects consumer experience within effortful tasks. The current research aims to examine this underexplored issue by investigating the effect of self-tracking on different consumer segments (i.e., females vs. males) within various cognitively effortful tasks (i.e., riddle, math, and word scramble quiz). A series of three experiments provides systematic support for the authors' hypotheses. Experiment 1 documents the stronger positive effect of self-tracking on females' (vs. males') perceived competence in an effortful task. Experiment 2 further documents the positive (vs. negative) effect of self-tracking on females' (vs. males') task experience, particularly enjoyment and subjective vitality, with direct process evidence that perceived competence mediates the observed effect. Finally, Experiment 3 demonstrates that overestimation attenuates the positive impacts of self-tracking on females' perceived competence and task experience within an effortful task.

6.1 Theoretical contributions

The current research makes two theoretical contributions. First, it sheds light on the role of self-tracking within effortful tasks. Although previous research (Etkin, 2016) has

suggested a negative impact of self-tracking on consumers' task enjoyment, such an effect has only been examined within effortless tasks. In addition, this work highlights the importance of individual characteristics (e.g., gender) in relation to the effect of self-tracking on consumer experience: for example, self-tracking has a positive (vs. negative) impact on females' (vs. males') task experience within effortful tasks. Furthermore, the authors offer process evidence that increased perceived competence drives the effect of self-tracking on task experience within effortful tasks. To the authors' knowledge, the current research is among the very few to empirically test and link the association between self-tracking and task experience via perceived competence.

Second, the current research contributes to the consumer experience literature. While previous studies have considerably focused on the consumer experience created by various contextual factors (e.g., ambient scent, physical environment, and visual stimulus; Cirrincione et al., 2014; Kumar, Dash, & Malhotra, 2018; Law, Wong, & Yip, 2012), this work explores a feedback mechanism—namely, self-tracking—and its downstream effects. In particular, the authors document self-tracking as an important marketing tool that influences consumer experience. This finding adds to the existing constellation of external stimuli that affect consumer experience.

6.2 Practical implications

Understanding and creating positive consumer experience is critical for marketers (Lemon & Verhoef, 2016). The current research suggests two useful marketing implications. First, manufacturers of self-tracking products (e.g., activity trackers) may want to add more features that allow consumers to track effortful activities (e.g., swimming, boxing), as self-tracking can generate positive consumer experience within effortful tasks. Note that it is important to take measures to keep these activities challenging (e.g., provide challenging goals), as once consumers develop a high performance expectancy, self-tracking may negatively influence their task experience. Marketers should also be cautious about implementing feedback intervention (e.g., praising messages) in their self-tracking products. Positive messages can be encouraging, but can also be detrimental to consumers' experience when the message

makes consumers overestimate themselves. At the same time, marketers can consider providing upward comparison feedback to prevent consumers from becoming overconfident, and thus mitigate the potential negative impact of self-tracking on consumer experience.

Second, marketers who plan to add self-tracking features into their existing products (e.g., workout equipment) may first want to consider what their main consumer segments are. If the majority of their customers are females, marketers may consider implementing self-tracking technologies into their products (e.g., smart jump rope). On the other hand, if the main customers are males, marketers may want to give it a second thought, as self-tracking products can negatively influence males' task experience. However, this is not to say that self-tracking will always be beneficial for females. For example, when females were made to overestimate themselves (e.g., in Experiment 3), self-tracking did not have a positive effect on their task experience. The current research implies that marketers may benefit from considering consumers with low self-confidence as their segment and targeting direction.

6.3 Limitations and avenues for future research

The current research has some limitations. First, three experiments in the current research were conducted on MTurk platform, and the sample representativeness may be questionable. While the participants in the current research represent a wide range of age groups and vocations, care should be taken in generalizing the results from one particular type of sample. Future research is needed to determine if these results hold in non-MTurk settings.

Second, the current research primarily focuses on the effect of self-tracking within cognitively effortful tasks. Although the authors expect analogical effects of self-tracking within physically effortful tasks, it would be important to empirically test such assumptions. Furthermore, as riddle and word scramble quiz can be considered as tasks that are initially fun, it would be interesting to examine the effect of self-tracking within boring or mundane tasks as well. Self-tracking feedback may help reduce task boredom

by providing interactive elements to the boring task, which would attenuate potential non-task-related mind wondering, and enhance task enjoyment.

Third, the current research examined the effect of self-tracking for initial task engagement. Repetitive task engagement may allow consumers to obtain certain reference points for their task performance based on their own previous experience or others' experience. Such a reference point may influence their task experience, as self-tracking feedback can now tell them how well they are performing (e.g., above vs. below reference point) at a given task. Reference point given prior to a task may also help form a more objective self-estimation, which can prevent consumers from overestimating themselves. This may in turn attenuate the potential negative effect of self-tracking on consumers' task experience. Future research can further investigate the role of reference point in altering the effect of self-tracking on consumers' task experience.

Lastly, another area for future research would be to examine the role of perceived autonomy in relation to the effect of self-tracking on task experience. Although the authors believe that the experimental designs in this study did not have any autonomy-threatening features, the observed negative impact of self-tracking on males' task experience calls for an additional investigation for the potential detrimental effect of self-tracking on consumers' perceived autonomy.

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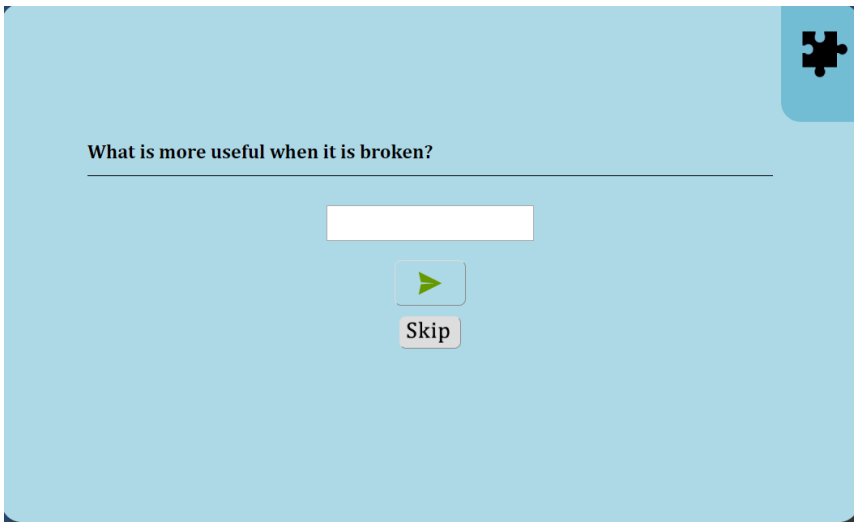
Paper 3: Appendix A. Website design in Experiment 1

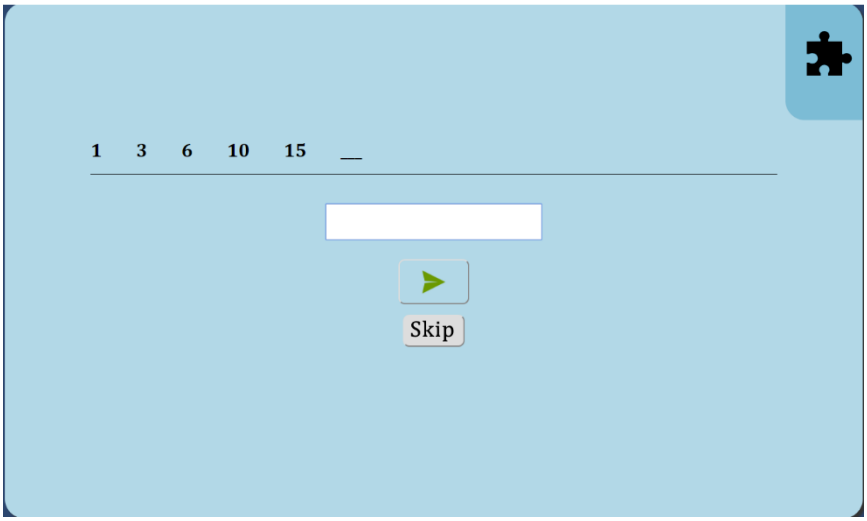
Control condition:



Quantification condition:

Paper 3: Appendix B. Website design in Experiment 2

Control condition:



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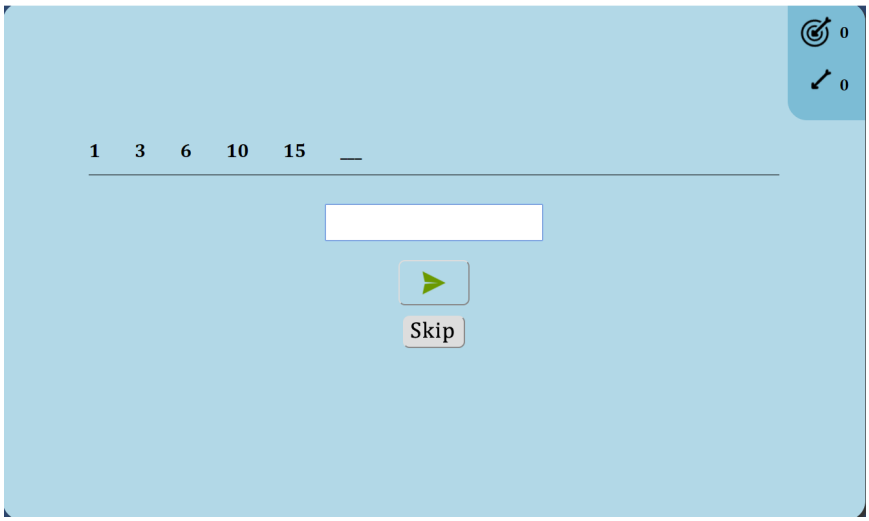
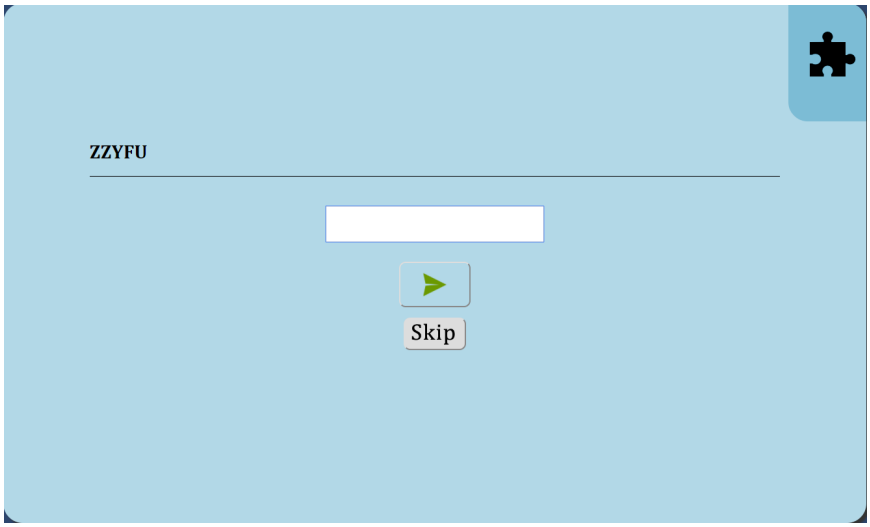


Paper 3: Appendix C. Website design in Experiment 3

Control condition:



Quantification condition: