Portraying Humans as Machines to Promote Health:

Unintended Risks, Mechanisms, and Solutions

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ABSTRACT

To fight obesity and educate consumers on how the human body functions, health education and marketing materials often highlight the importance of adopting a cognitive approach to food. One strategy employed to promote this approach is to *portray humans as machines*. Five studies (and three replication and follow-up studies) using different human-as-machine stimuli (internal body composition, face, appearance, and physical movement) revealed divergent effects of human-as-machine representations. While these stimuli promoted healthier choices among consumers who were high in eating self-efficacy, they backfired among consumers who were low in eating self-efficacy (measured in Studies 1 and 3–5; manipulated in Study 2). This reversal happened because portraying humans as machines activated consumers' *expectation* of adopting a cognitive, machine-like approach to food (Studies 3 and 4)—an expectation that was too difficult to meet for those with low (vs. high) eating self-efficacy. We tested a solution to accompany human-as-machine stimuli in the field (Study 5): Externally enhancing how easy and doable it was for consumers low in eating self-efficacy to meet the expectation of adopting a cognitive approach to food, which effectively attenuated the backfire effect on their lunch choices at a cafeteria.

Keywords: eating self-efficacy, health, human-as-machine representations, dehumanization, machine, artificial intelligence, (performance) expectation

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More than two-thirds of adults and one-third of preschoolers in the United States are overweight or obese (Centers for Disease Control and Prevention 2015); similar rates exist in many other countries worldwide (World Health Organization 2016). To combat obesity, governments, marketers, and consumer welfare organizations invest a great amount of resources to encourage consumers to make food choices in a cognitive manner and to use their head instead of their heart (e.g., "Eat to fuel your body, not to feed your emotions"). These cognitive, head-based approaches to food such as reading nutrition labels and computing calories are believed to be optimal health strategies (Food and Agriculture Organization 2004; World Health Organization 2016). Accordingly, major health interventions and programs have invested a lot of resources to promote these cognitive approaches that are analytical, rule-abiding, and free of emotions (Gerrior, Juan, and Basiotis 2006; Kozup, Creyer, and Burton 2003; Parker and Lehmann 2014; Reyna et al. 2009).

One popular strategy employed to promote a cognitive approach to food is to *portray humans as machines* and to depict human body parts using mechanistic components. A wide variety of examples can be found in the recent campaigns by the American Heart Association, the Centers for Disease Control and Prevention (CDC), Men's Health Week, and GBCHealth (see Web Appendix 1 for a list of recent health campaigns using human-as-machine stimuli). These materials try to leverage people's existing associations about machines—that machines make decisions based on their head (cognition) and not their heart (emotion)—to help consumers approach food in a more cognitive, machine-like manner, with the goal of encouraging healthier choices. *National Geographic's* series "The Incredible Human Machine" even describes unhealthy behaviors as (human) "errors" in the maintenance of our bodily machine.

Similarly, companies and marketers have started using human-as-machine representations. For instance, Centrum asks consumers to “power the human machine” with healthy food supplements. Nestlé encourages indulgence as the “human” (vs. a machine-like) thing to do; their tagline “Working like a machine? Have a Kit Kat” motivates consumers to be more like humans and have a chocolate bar—a choice that rational machines would not make (see Web Appendix 1 for additional examples by Snickers, Red Bull, Anheuser-Busch, and others).

Furthermore, consumers experience human-as-machine representations not only in targeted advertisements, but also in everyday life. With fast improvements in technology, virtual telepresence systems show people as human faces with mechanistic bodies, human enhancement technologies (e.g., augmented reality goggles, transcranial simulation headbands) represent humans as more machine-like, and Artificial Intelligence software further blurs the line between humans and machines (Castelo, Schmitt and Sarvary 2019; Longoni, Bonezzi, and Morewedge 2019; Luo et al. 2020). These technological advances are entering the retail sector and restaurants (O’Reilly 2017) and are driving consumption decisions.

Despite the existence of human-as-machine representations in public policy, education, food marketing, and consumers’ daily lives, research has yet to systematically examine how consumers react to such representations. The examples above suggest a possible lay belief among practitioners that by making humans look more like machines, people would choose food in a cognitive manner and thus make healthier choices. How accurate is this lay belief? We aim to answer three questions in this research: (1) Does representing humans as machines indeed encourage healthier choices? (2) Might there be heterogeneity in how consumers respond to these stimuli? (3) What psychological processes drive these effects?

To this aim, we spotlight an important individual difference variable: consumers' *eating self-efficacy* (i.e., confidence in one's own ability to choose healthy food; also referred to as healthy or healthful eating efficacy, healthy diet efficacy, and dieting self-efficacy; Armitage and Connor 1999, Stotland, Zuroff, and Roy 1991). We theorize that, contrary to practitioners' lay belief, human-as-machine representations could create divergent effects on consumers' food choices, depending on a person's chronic level of eating self-efficacy.

This hypothesized divergent effect is driven by the following process: (1) Being exposed to human-as-machine stimuli brings to mind the *expectation* that one should behave more machine-like, i.e., adopting a cognitive, head-based approach to food; (2) importantly, this expectation can be motivating (i.e., leading to healthier choices) only if consumers believe that they can meet it. While consumers with high levels of eating self-efficacy believe in their abilities to choose food in a cognitive, machine-like manner (and thus would be motivated to fulfill this expectation), consumers with low levels of eating self-efficacy tend to struggle with a cognitive approach to food. As a result, this latter and more vulnerable consumer segment would anticipate failure in fulfilling this expectation, leading them to go against it and choose unhealthier options (Brehm 1966; Brehm and Brehm 1981; Byrne and Hart 2009; Reynolds-Tylus 2019). As low levels of eating self-efficacy have been linked to overweight and obesity (Friedman and Brownell 1995), the very segment that the human-as-machine marketing communication aims to educate is the one that does not benefit from this approach, revealing a critical dark side of these representations on consumers' well-being.

A Cognitive, Machine-Like Approach to Food

Obesity has been considered one of the most critical global crises in the 21st century, with detrimental health consequences to individuals as well as serious economic costs collectively (World Health Organization 2016). As a result of this, governments, policy makers, NGOs, and marketers have developed a variety of materials and programs to encourage consumers to make healthier food choices. One key trend in these materials and programs is to push toward a more cognitive approach to food (Gerrior, Juan, and Basiotis 2006; Kozup, Creyer, and Burton 2003; Parker and Lehmann 2014; Reyna et al. 2009); for instance, to encourage consumers to choose food with their head and not their heart (e.g., "H.A.L.T. before eating" in which H.A.L.T. stands for hungry, angry, lonely, and tired), and to highlight the importance of nutrition labels and calorie tracking (World Health Organization 2016). The rise of AI-based technologies and devices in the health industry (Puntoni et al. 2020) further promotes that health-related decisions (such as food choices) should be based on analytics and that considering humans' unique characteristics and emotions might hinder optimal decision making (Longoni, Bonezzi, and Morewedge 2019).

In line with this general push toward a cognitive approach to food, one popular strategy is to portray humans as machines and depict human body parts using mechanistic components (see Web Appendix 1). This process of altering humans' physical dimensions to make humans look more like machines is conceptualized as *mechanistic dehumanization* (Haslam 2006; Haslam and Loughnan 2014) and can be treated as a reverse process to anthropomorphism (i.e., making objects/machines look more like humans; Aggarwal and McGill 2007; Epley, Waytz, and Cacioppo 2007). While anthropomorphism has received considerable attention in the marketing literature (Aggarwal and McGill 2007; Landwehr, McGill, and Herrmann 2011), dehumanization is mostly studied in psychology with a focus on intergroup relations and threat as a top-down, motivated bias that affects how ingroup members may compare outgroup members to objects/machines (Gray, Gray, and Wegner 2007; Haslam and Loughnan 2014; Leyens et al. 2000; Waytz et al. 2010).

More recent work has begun to acknowledge that perceptions of machine-likeness in humans can also be driven by a bottom-up process, such as through an exposure to a visual cue (without specific intergroup conflicts or biases). For instance, facial configurations (e.g., width-to-height ratio, Deska, Lloyd, and Hugenberg 2018; see also Hugenberg et al. 2016; Looser and Wheatley 2010) or movement speed (Heptulla Chatterjee, Freyd, and Shiffrar 1996; Shiffrar and Freyd 1990) can influence how machine-like a human is perceived. Our work builds on these recent findings by (1) exploring other dimensions that can shift how humans are perceived, i.e., changing the body composition, and appearance, (2) homing in on the impact of representing humans as machines on food choices that consumers make daily, beyond the traditional context of intergroup relations and threat, and (3) further theorizing the driving role of consumers' idiosyncratic differences in eating self-efficacy.

Importantly, we argue that being exposed to human-as-machine representations, with more machine-like (1) internal body composition, (2) face, (3) appearance, and (4) physical movement, can affect consumers' choices, because it changes their expectation of how they should behave when it comes to food.

An Expectation to Choose Food Like the "Tin Man" Would

We posit that being exposed to human-as-machine representations changes not only consumers' perceptions but also their *expectations* of how they should behave. This is because alterations of physical features elicit schemas (either of humans or machines) and prompt individuals to apply normative behavioral expectations accordingly (Aggarwal and McGill 2007; 2012; Kim and Kramer 2015; Kim and McGill 2011). For instance, machines that look more human-like, such anthropomorphized computers are expected to interact like humans, such as making small talk (Cassell and Bickmore 2000), and anthropomorphized automobiles are trusted more (Waytz, Heafner, and Epley 2014). In contrast, humans being portrayed as machines brings to mind the expectation that one should behave like a machine. If a runner is portrayed as a machine, one expects this runner to be a strong entity without "human weakness" (Gleyse 2013; Hoberman 2001). Patients who are perceived as machines are expected to experience less "human" pain, which would allow doctors to maintain their professional distance and objectivity (Haque and Waytz 2012; Kumar et al. 2014).

While humans can surely hold a variety of schemas and expectations about machines, one of the most prominent schemas, we conjecture, is that machines rely solely on their head (cognition), as they lack a human heart (emotion); in contrast, emotion and cognition are both fundamental elements of humans' decision making (Cian, Krishna, and Schwarz 2015). These associations are formed from early childhood and are continuously reinforced through common language usage and mass media. For instance, in *The Wizard of Oz*, all that the tin man wants is a human heart, because as a robot, he has only a brain. Data, the machine on *Star Trek*, wants to let go of rationality to experience human emotions. Likewise, when a human possesses machine-like features, such as Iron Man (Tony Stark), he struggles with the effects of becoming too rational and losing human emotionality.

To empirically verify consumers' existing schema that machines rely on their head (cognition) and not their heart (emotion), we conducted a pilot study and asked 305 US-based adults and students (46.6% female, $M_{age} = 36.08$), on three 7-point scales, to what extent they consider machines' decisions and humans' decisions to be based on emotion (1 = *emotional, non-analytical, warm*) compared to cognition (7 = *unemotional, analytical, cold*; Haslam 2006; Haslam et al. 2005; Cronbach's alpha = .92). Results verified that people believed that machines' decisions were more cognitive and head-based (M = 6.35, SD = .84) than humans' decisions (M = 3.34, SD = 1.26), $t(303) = 24.87$, $p < .001$, d = 2.82. We also included the classic Heart vs. Mind Scale (Shiv and Fedorikhin 1999; Cronbach's alpha = .94), and found that these two sets of scales were highly correlated ($r(303) = .85$, $p < .001$) and provided consistent results: Machines' decisions were perceived as being based more on thoughts, cognition, and the head (M = 4.57, SD = 1.20) than humans' decisions (M = 2.00, SD = 1.35), t(303) = 17.20, $p < .001$, d = 1.97.

We posit that this popular association that machines rely on their head (cognition) can activate an expectation for one's own behaviors because the human-as-machine stimuli either explicitly or implicitly establish a connection between humans and machines. By visually transforming humans' body composition, appearance, and movement characteristics into machines, the human-as-machine stimuli bring to mind schemas about machines (e.g., a cognition-driven decision approach) and activate an expectation that these schemas should apply to humans, much the way anthropomorphism—by portraying objects as humans—activates an expectation that human schemas should apply to the focal objects (Aggarwal and McGill 2007; 2012; Kim and Kramer 2015; Kim and McGill 2011).

In sum, we posit that when humans are portrayed as machines in health or food marketing, it activates an expectation that one should behave like a machine, relying on one's head (cognitive) instead of the heart (emotion) when choosing food. Importantly, we argue that this expectation can lead to more complicated consequences than originally anticipated: The effect depends on consumers' chronic level of eating self-efficacy.

The Driving Role of Self-Efficacy in Eating Behavior

Having an expectation of making cognitive, machine-like food choices can motivate healthier choices only if consumers believe that the expected behavior is doable (Atkinson 1957; Liberman and Förster 2008; Oettingen et al. 2004). Specifically, when facing an expectation, consumers go through an evaluation process, in which they assess their abilities to successfully meet the expectation (e.g., using their past behaviors as a proxy; Bandura 1991). This evaluation process thus involves predicting future outcomes to determine one's choices and behaviors. If consumers believe that they can meet the expectation, they then anticipate success in fulfilling this expectation (Bandura 1991; Bandura and Cervone 1983) and the anticipation of success operates as a positive motivator, facilitating the engagement of behaviors that will help to meet the expectation (Bandura 1997; Bandura and Schunk 1981; Liberman and Förster 2008).

In contrast, if consumers believe that they cannot meet the activated expectation (e.g., because their past performances were unsuccessful), they instead anticipate failure in fulfilling this expectation (Bandura 1991; Bandura and Cervone 1983). The anticipation of failure, critically, serves as a negative motivator (Bandura 1991; Bandura and Cervone 1983), leading to disengagement (Huang and Zhang 2011; Locke and Latham 2002) and often opposite behaviors. Two lines of research suggest that a backfire effect—going against the activated expectation to choose unhealthier food—would likely occur in this case. First, anticipating failure can trigger aggression towards the self and reactance against the activated standard or expectation (Brehm 1966; Brehm and Brehm 1981). Because an impossible standard/expectation induces feelings of impairment regarding one's abilities, people would opt to reestablish their freedom by behaving "in the way they want" (and not in the way they are expected to, Reynolds-Tylus 2019). In the context of health, this would result in a backfire or boomerang effect that goes against the communicated message (Byrne and Hart 2009; Reynolds-Tylus 2019). Second and more specific to the food domain, knowing that one will fall short of an internal or external expectation leads to an unflattering and aversive evaluation of the self, which is often accompanied by negative emotions and emotional distress (Baumeister 1997; Heatherton, Herman, and Polivy 1991). Dietary disinhibition and overeating can then occur as a way to escape from these unpleasant states (Mills et al. 2002; Seddon and Berry 1996; Strauss, Doyle, and Kreipe 1994). Feeling unable to meet the body-shape expectations activated by a super thin magazine model, for instance, led women to unhealthy overeating to make themselves feel better (Klesse et al. 2012).

Many traits can affect how consumers respond to the expectation of making cognitive, machine-like food choices. We propose that consumers' chronic level of eating self-efficacy constitutes one critical trait. Self-efficacy is broadly defined as belief in one's ability to achieve a particular outcome or goal (Bandura 1997). Eating self-efficacy, accordingly, refers to a consumer's belief in his or her specific ability to choose healthy food (Armitage and Connor 1999; Stotland, Zuroff, and Roy 1991).

More importantly, eating self-efficacy is linked to several eating habits essential to a cognitive, machine-like approach to food. Consumers high (vs. low) in eating self-efficacy are less likely to succumb to emotional eating (Costanzo et al. 2001; Toray and Cooley 1997), or to use food to respond to negative emotional events (i.e., an argument with family, Stich, Knäuper, and Tint 2009) and anxiety (Clark et al. 1991; Glynn and Ruderman 1986). While consumers low in eating self-efficacy use food to deal with boredom (Glynn and Ruderman 1986), those high in eating self-efficacy have less difficulty staying focused on the functional (cognitive) aspect of food. Similarly, consumers high (vs. low) in eating self-efficacy do better with analytics-based consumption, such as estimating portion size (Knäuper 2013), evaluating caloric needs (Stotland, Zuroff, and Roy 1991), and calculating nutritional values (Wilson-Barlow, Hollins, and Clopton 2014).

Since existing habits and past behaviors are the basis for assessing one's ability to meet an expectation (Bandura 1991), it is likely that consumers chronically high in eating self-efficacy would consider a cognitive, machine-like approach to food to be an easy expectation to meet, whereas the same standard would seem extremely difficult or impossible for consumers low in eating self-efficacy. We empirically verified this in another pilot study: Consumers high (vs. low) in eating self-efficacy indeed felt more (vs. less) able to make food decisions in a cognitive, machine-like manner; see Web Appendix 2 for method and results of the pilot study.

To summarize, we propose the following three hypotheses:

H1: Exposure to human-as-machine (vs. human or control) representations leads to healthier (vs. unhealthier) food choices for consumer high (vs. low) in eating self-efficacy.

H2: Exposure to human-as-machine (vs. human or control) representations activates an expectation that one should adopt a cognitive, machine-like approach to food.

H3: Consumers high (vs. low) in eating self-efficacy feel able (vs. unable) to meet the activated expectation of adopting a cognitive, machine-like approach to food, resulting in healthier (vs. unhealthier) food choices.

Figure 1 illustrates our conceptual model.

Insert Figure 1 about here

Overview of Studies

We conducted five studies (and three replication and follow-up studies) with a variety of incentive-aligned food choices and a variety of human-as-machine stimuli. Study 1 (and two replications) and Study 2 tested our key hypothesis: Human-as-machine representations led to healthier and unhealthier food choices based on consumers' level of eating self-efficacy (H1). We measured consumers' chronic level of eating self-efficacy in Study 1 and directly manipulated eating self-efficacy in Study 2.

Studies 3 and 4 (and a follow-up study) tested the proposed mechanisms through moderated mediation analyses: Exposure to human-as-machine stimuli activated an expectation to approach food in a cognitive, machine-like manner in all consumers (H2). Activating this expectation led to divergent effects—whereas consumers high in eating self-efficacy made healthier food choices, consumers low in eating self-efficacy went against the expectation and made unhealthier choices (H3). Studies 3 and 4 also ruled out alternative accounts such as perception of food (as a source of pleasure or energy), hunger, what people believed they could digest, emotionality, and perception of humans' competence.

Lastly, Study 5 explored a theory-based solution in the field by accompanying human-as-machine stimulus with a message that made consumers feel that they *can* meet the expectation to make food choices in a cognitive, head-based manner. The intervention message successfully attenuated the backfire effect on lunch choices at a cafeteria and allowed an effective use of human-as-machine stimuli to facilitate healthier choices for all.

Study 1: Human-as-Machine Body Stimuli and Food Choices

Study 1 tested our key proposition, that human-as-machine representations would facilitate healthier choices among consumers high in eating self-efficacy but would backfire and result in unhealthier choices among consumers low in eating self-efficacy (H1). In order to set a baseline of what people choose without exposure to any stimulus related to humans or machines, we also included a control condition in which participants viewed a neutral visual.

Method

Participants. Three hundred UK-based adults (64.0% female, $M_{age} = 36.70$) recruited from Prolific Academic participated in this study. The study used a 3 (Stimulus: human-as-machine vs. human vs. control) × Eating Self-efficacy (measured as a continuous variable) between-subjects design. For this and all following studies, target sample sizes were determined in advance of data collection based on participant availability, study design, and collection method (Simmons, Nelson, and Simonsohn 2011). We reported all data exclusions, manipulations, and measures; all stimuli can be found in Web Appendix 3, and all datasets are available upon request.

Stimulus design and pretest. Inspired by health marketing stimuli used in the real world (see Web Appendix 1) and following procedures from anthropomorphism research (McGill 1998), we created human-as-machine stimuli by altering an image of the human digestive system (i.e., the internal body composition) in this study. In the human-as-machine condition, the digestive system was illustrated as a machine; in the human condition, the digestive system was illustrated as human organs. For the stimulus pretest, we also included a third human condition—a human upper body with no organs showing, to ensure that showing human organs in the human condition did not make the image seem less human (see Web Appendix 3 for all stimuli).

In the stimulus pretest, we measured human versus machine perception using scales from the anthropomorphism literature (Aggarwal and McGill 2007; Kim and McGill 2017; Romero and Craig 2017). Participants rated one of the images on three 7-point Likert scales: "The human (body)…1 = *looks like a machine*, 7 = *looks like a human*; 1 = *does not look alive at all*, 7 = *looks very alive*; 1 = *contains mainly machine-like features*, 7 = *contains mainly human-like features*." For comprehensiveness, we also included classic measures of dehumanization: "The human (body) is represented as unemotional, cold, rigid, fungible (lacking individuality), superficial, passive, inert (lifeless)"; 1 = *strongly disagree*, 7 = *strongly agree* (Haslam, 2006). The results verified that the digestive system presented as a machine was indeed perceived as more machine-like on the human–machine continuum (M = 3.54, SD = 1.81) than the digestive system presented as human organs (M = 5.18, SD = 1.24; t(64) = 5.51, $p < .001$, d = 1.36) and the human upper-body condition (M = 5.08, SD = 1.41; t(64) = 4.82, $p < .001$, d = 1.19); the latter two groups did not differ (t(64) = .31, $p = .759$, d = .08). Results were similar for the reverse-coded dehumanization scale (see Web Appendix 3 for results and scale correlations). Based on the pretest results, we used the images of the two digestive systems (without the upper-body) in the main study to test the hypothesized effect.

Procedure. In the main study, participants were told that they would view different visuals and representations of the human body and that they would share their honest thoughts and opinions about them. After completing a bot check, they saw one of the two images from the pretest (digestive system presented as a machine vs. as human organs). Following the procedures in prior literature (Gino, Kouchaki, and Galinsky 2015; Smith et al. 2008), we had participants describe the digestive system in 100 words based on the image they saw, to reinforce the manipulation and ensure attention to the stimulus. We also included a pure (no human and no machine) control condition, in which participants saw a map and were asked to describe the directions from home to their work place in 100 words. The control condition ensured a similar amount of writing effort with no specific relation to either machine or human, allowing us to isolate the direction of changes in participants' food choices. Participants responded to two filler questions to reduce demand effects (see Web Appendix 4 for the variety of filler questions used in this and the following surveys).

To capture food choices, all participants were told at the end of this survey that, in addition to their regular compensation, they would be entered into a lottery for $9 worth of food coupons. They were asked to choose three snack items (each in a $3 portion size) out of a selection of 10, and were promised the coupons for the three items they chose (incentive-compatible). For each snack item, participants read information on ingredients and caloric content per package. The calorie content of these 10 items ranged from 30 (mini peeled carrots) to 250 (Snickers bar; see Web Appendix 5 for snack choices used). Participants selected three items and received a confirmation that they were now entered into the lottery.

Participants then proceeded to another set of filler questions before responding to the four-item eating self-efficacy scale by Armitage and Connor (1999), such as "I believe I have the ability to eat a low-fat diet in the next month" (1 = *definitely do not*, 7 = *definitely do)* and "If it were entirely up to me, I am confident that I would be able to eat a healthy diet in the next month" (1 = *strongly disagree*, 7 = *strongly agree*; Cronbach's alpha = .91; see Appendix for the full scale). Before exiting the study, participants entered demographic information and reported any suspicion or question they had. All participants were debriefed and entered a lottery to receive $9 additional payment (the monetary value of the coupons).

Results and Discussion

None of the participants raised any suspicion or questions. We summed the calorie content of the three snack items the participants chose as a proxy for how healthy their food choices were, as prior literature has shown that consumers use calorie information to assess the healthiness of food items (Chernev and Chandon 2010). To ensure that this was indeed the case, we also conducted a posttest on the health perception of these 10 snacks (see Web Appendix 5 for posttest result of the snacks). Replacing the sum of calories with the sum of health scores from the posttest as the dependent measure revealed consistent results.

We conducted a regression analysis with stimulus (human-as-machine vs. human vs. control), eating self-efficacy (continuous measure), and their interaction as predictors, with age and gender serving as control variables (Model 1, Hayes 2013). In this and all following studies, we included age and gender as covariates as both have been shown to affect how people feel about machines (Bartneck et al. 2007; Nomura, Kanda, and Suzuki 2006) as well as how they make food choices (Ares and Gámbaro 2007). Analyses without these variables revealed consistent patterns in all studies. We report results without age and gender in Web Appendix 6 for comprehensiveness.

The model revealed a main effect of eating self-efficacy ($\beta = -45.22$, SE = 8.86 t = -5.11, $p < .001$); people with higher eating self-efficacy chose lower-calorie snacks. The model also revealed two main effects of stimulus (human-as-machine vs. control: $\beta = 270.48$, SE = 71.50, t = 3.78, $p < .001$, and human-as-machine vs. human: $\beta = 205.09$, SE = 81.32, t = 2.52, $p < .001$); human-as-machine stimulus led participants to choose higher-calorie snacks compared to the other two conditions. With regard to control variables, results revealed that female participants chose lower-calorie snacks ($\beta = -32.37$, SE = 14.19, t = -2.28, $p = .023$).

Age did not have an effect. More important, we found two significant Stimulus × Eating Self-efficacy interactions, one between the human-as-machine condition and the human condition, β = −36.84, SE = 14.19, t = −2.66, p = .008, and another between the human-as-machine condition and the control condition, β = −50.32, SE = 12.56, t = −4.01, $p < .001$.

Further spotlight analyses on eating self-efficacy (M = 5.62, SD = 1.27) illustrated that among those with high eating self-efficacy (1 SD above the mean = 6.89), the effect of the human-as-machine stimulus was facilitative such that participants chose lower-calorie snacks in the human-as-machine condition (M = 475.40) than in the control condition (M = 551.41), β = −76.01, SE = 23.89, t = −3.18, p = .002, or the human condition (M = 523.92), β = −48.52, SE = 23.03, t = −2.11, p = .036; the human and control condition did not differ, β = −27.48, SE = 24.56, t = −1.12, p = .264. In contrast, the human-as-machine stimulus backfired among participants with low eating self-efficacy (1 SD below the mean = 4.35), such that they chose higher-calorie snacks after viewing the human-as-machine stimulus (M = 590.28) than after viewing either the control stimulus (M = 538.44), β = 51.84, SE = 22.46, t = 2.31, p = .022, or the human stimulus (M = 545.22), β = 45.05, SE = 25.54, t = 1.76, p = .079; the human and control conditions did not differ, β = 6.78, SE = 24.34, t = .28, p = .781 (see Figure 2).

Insert Figure 2 about here

We further replicated these results in two follow-up studies with a different eating self-efficacy scale to increase generalizability. Self-efficacy and behavioral control are conceptually similar and often used interchangeably (Droms and Craciun 2014). Accordingly, we adopted a measure from the behavioral control literature and used five items of Moorman and Matulich's (1993) scale that directly assessed eating self-efficacy; sample items included "It's easy for me to reduce my sodium intake" and "It's easy to eat fresh fruits and vegetables regularly" (1 = *strongly disagree*, 7 = *strongly agree*; Cronbach's alpha =

.74). In the first follow-up study, exactly mirroring Study 1, we captured participants' chronic level of eating self-efficacy at the very end of the survey session so that its measurement would not contaminate participants' interpretation of the stimuli or their food choices. In the second follow-up study, we measured participants' chronic level of eating self-efficacy first, then added filler items, and then exposed participants to the human-as-machine stimuli to account for any demand effects. See Web Appendix 7 for method and results of these studies.

The results of Study 1 and the two replications provided support for the divergent effects of portraying the human body as a machine (H1), revealing a critical dark side of such representation. While consumers with a high level of eating self-efficacy reacted positively to this stimulus and made healthier choices, consumers with a low level of eating self-efficacy made worse food choices upon exposure to human-as-machine representations.

Study 2: Directly Manipulating Eating Self-efficacy

Study 2 served two objectives. First, we tested a different human-as-machine stimulus to enhance the generalizability of the support for H1—the face, which is often used in anthropomorphism research (Kim and McGill 2011; Landwehr, McGill, and Herrmann 2011) and has been a keen focus of previous dehumanization research (e.g., Deska, Lloyd, and Hugenberg 2018). We added machine-like features to a human face and tested the effect of this stimulus on food choices. This also served to ensure that the observed divergent effects would occur without seeing a visual of the digestion system. Second, we directly manipulated individuals' perceived level of eating self-efficacy to rule out any other dispositional differences between these two types of consumers as alternative accounts.

Method

Participants. Two hundred three undergraduate students (43.8% female, M_{age} = 20.32) came into the lab of a large Dutch university to participate in this study in exchange for study credits. The study used a 2 (Stimulus: human-as-machine vs. human) × 2 (Eating Self-efficacy: high vs. low) between-subjects design.

Stimulus design and pretest. Following the procedures in Study 1, participants in the pretest were randomly assigned to one of two conditions. In the human-as-machine condition, participants saw a human face with machine-like features. In the human condition, participants viewed the same human face without machine-like features. In both conditions, participants saw either a male or female face. The pretest using the same two machine-likeness and dehumanization scales as in Study 1's pretest (Aggarwal and McGill 2007; Haslam 2006; Kim and McGill 2017; Romero and Craig 2017) was successful. Those who saw the human-as-machine face evaluated the face as more machine-like than those who saw the human face (see Web Appendix 3 for stimuli pretest details and results).

Procedure. In the main study, participants were told that there were multiple different surveys in the study and that they would complete all of them in order. They first went through a general survey about themselves, which incorporated an eating self-efficacy manipulation that we developed based on work by Bandura and Jourden (1991) and Ben-Ami et al. (2014). Participants answered a set of questions regarding their current eating habits (e.g., "How many of your meals in an average week include red meat," "How many of your weekly meals are likely high in sodium (because they are canned, packaged, or take-out options)." They were then informed that a score was calculated based on their answer to these questions, reflecting how capable they were of eating healthily; participants were randomly assigned to see that they were classified as "very capable" (high eating self-efficacy) or "having difficulties" (low eating self-efficacy). See Web Appendix 8 for the manipulation.

After completing the eating self-efficacy manipulation, participants entered the second study, in which we randomly exposed them to either the human-as-machine face or the human face. Participants were *not* asked to write 100 words about the stimuli in this study, to further ensure that the observed effects could occur without mandatory reflection.

Lastly, participants were asked to choose three snacks (each in a $3 portion size) out of a selection of 10, as in Study 1. We further included both eating self-efficacy scales as manipulation checks: the scale used in Study 1 (Armitage and Connor 1999, Cronbach's alpha = .92) and the scale used in the two replications (Moorman and Matulich 1993, Cronbach's alpha = .64). The manipulation was successful (see Web Appendix 8 for results).

The session ended with demographic information and probing for suspicion and questions. All participants entered a lottery for $9 additional payment. As we informed some participants they weren't eating healthily, we included an extensive debrief and ensured that all participants read and understood that the score was arbitrary and unrelated to their actual behavior. We also allowed them to withdraw their data from analysis if desired (out of 203 undergraduate students, seven opted to not be included, leaving a final sample of 196).

Results and Discussion

We conducted an ANCOVA with stimulus (human-as-machine vs. human), eating self-efficacy (high vs. low), and their interaction as predictors, and age and gender as covariates. We again found a main effect of eating self-efficacy: Participants who believed they were low in eating self-efficacy chose higher-calorie snacks (M = 475.88, SD = 139.96) than those who believed that they had high eating self-efficacy (M = 420.00, SD = 134.61, $F(1, 190) = 7.63$, $p = .006$, $\eta^2 = .039$). There was no main effect of stimulus, age, or gender in this study. Consistent with Study 1, we again observed the hypothesized Stimulus × Eating Self-efficacy interaction, $F(1, 190) = 5.15$, $p = .024$, $\eta^2 = .026$.

Further contrast analysis revealed that among the participants who were led to perceive high eating self-efficacy, the caloric content of the snacks chosen was similar between the human-as-machine face condition (M = 404.25, SD = 132.74) and the human face condition (M = 434.23, SD = 135.98), t(97) = 1.11, *p* = .270, d = .22. In contrast, those who were led to perceive low eating self-efficacy chose snacks significantly higher in calories when seeing the human-as-machine face (M = 505.77, SD = 139.04) than seeing the human face (M = 441.33, SD = 134.38), t(95) = 2.32, *p* = .023, d = .47 (see Figure 3).

Insert Figure 3 about here

Different from Study 1 and the two replications, those who were manipulated to have a high level of eating self-efficacy did not make healthier choices upon exposure to the human-as-machine stimuli. Since we did not observe this pattern in any of our other studies, we will discuss this discrepancy in the General Discussion. Overall, Study 2 used another type of human-as-machine stimulus—a machine-like human face—and directly manipulated people's perceived level of eating self-efficacy; we found that while the results among those who were led to perceive high eating self-efficacy was different, the backfire effect was replicated for those who were led to perceive themselves to be bad at eating healthily.

We hypothesized that viewing the human-as-machine stimulus led to divergent effects depending on consumers' levels of eating self-efficacy because (1) the stimulus brings to mind an *expectation* to choose food in a cognitive, machine-like manner, and that (2) this expectation motivates consumers with high eating self-efficacy (who feel capable of meeting the expectation) to make healthier choices, but conversely leads consumers with low eating self-efficacy (who feel incapable of meeting the expectation) to act against it, resulting in unhealthier choices. In Study 3, we used the same human-as-machine stimulus as in Study 1 to capture the activated expectation; in Study 4, we used another type of human-as-machine stimulus to triangulate the proposed role of expectation. Both studies further ruled out multiple alternative accounts including the perception of food as a source of pleasure or energy, hunger, what people believed they could digest, emotionality, and perception of humans' competence.

Study 3: The Role of Expectation

Study 3 served multiple purposes. First, we used a moderated mediation approach to provide support for the role of expectation, namely, that exposure to a human-as-machine stimulus creates an expectation that one should adopt a cognitive, machine-like approach to food in all participants (H2), and that this expectation leads to divergent food choices based on participants' chronic levels of eating self-efficacy (H3).

Second, we wanted to rule out several food-related alternative accounts such as the human-as-machine representations changing how hungry participants felt and what they believed their body could digest. We also wanted to ensure that our stimuli did not affect how the participants thought about food (as a source of pleasure or energy). Therefore we measured these alternative accounts for moderated mediation analyses, and also used a different set of food choices that varied in health perceptions but not in calorie content, to further underscore that it was indeed "unhealthy" food choices, rather than high-energy food choices (which often correlate with high calories) that led to the observed divergent effects.

Third, we aimed to underscore the importance of seeing a *human-as-machine* representation, and not just a general prime of machine, to activate the expectation for how humans should behave when choosing food. Hence, we added a machine-only condition without relating it to humans to explore this possibility.

Method

Participants. Two hundred ninety-five undergraduate students (47.8% female, M_{age} = 20.46) participated in this lab study for study credits at a large Dutch university. The study used a 3 (Stimulus: human-as-machine vs. machine-only vs. human) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Procedure. Following the procedures in previous studies, participants in the main study first viewed one of the stimuli of Study 1 (the digestive system: human-as-machine vs.

human), or a machine-only stimulus (with no visual reference to the human body, see Web Appendix 3). We again had participants describe the digestive system in 100 words based on the image they saw, to reinforce the manipulation and ensure attention to the stimulus (Gino, Kouchaki, and Galinsky 2015; Smith et al. 2008). In addition to ensuring attention, this approach also allowed us to register the amount of time spent on writing (Kellogg 1987), to assess if any condition evoked greater effort than others (which could lead to unhealthier choices because of perceived reward entitlement, Racine et al. 2019). Participants answered a filler question to further minimize the possibility of a demand effect.

Afterward, participants were told that for their participation, they could choose one snack to bring home and viewed four snack options available for that day's session: an energy bar, a yogurt, a chocolate bar, and a bag of chips (see Web Appendix 5 for snack choices). Based on our posttest (n = 107, 67.3% female, M_{age} = 27.05), the first two snacks were perceived as similarly healthy whereas the latter two were similarly unhealthy; calorie content was exactly the same across these snacks (see Web Appendix 5 for the posttest). Using a different set of snack options further enhanced the generalizability of our findings.

To cleanly capture the role of expectation, participants then went through another filler task and continued to the next part of the study. We were particularly interested in assessing if 1) exposure to human-as-machine stimulus that did not specifically mention food or eating would activate an expectation about how *food choices* should be made, and 2) participants applied the activated expectation to *themselves* and not just to humans in general. Hence, we asked the participants to report their perceived expectation of adopting a cognitive, machine-like approach to food on three 7-point Likert scales (Haslam 2006; Haslam et al. 2005; 1 = *strongly disagree*, 7 = *strongly agree*; Cronbach's alpha = .71): "I feel that I am expected to make my food choices. . .unemotional, analytical, cold." Participants were also asked to judge the function of food (pleasure or energy), their body's ability to digest a variety of food (Cronbach's alpha = .85), and their current hunger level (see Appendix for all scales). All scales of potential process variables were presented in random order.

The session ended with demographic information and the eating self-efficacy scale used in Studies 1 and 2 (Armitage and Connor 1999, Cronbach's alpha = .95), and probing for suspicion and questions. All participants received a snack when exiting the lab.

Results and Discussion

Food choice. None of the participants raised any suspicion or questions about the study. Since all snack options contained the same amount of calories, we coded the choice of healthy snack as 0 and unhealthy snack as 1 to be consistent with previous studies (i.e., higher values represented unhealthier choices) and submitted this binary dependent variable to an analysis with stimulus (human-as-machine vs. machine-only vs. human), eating self-efficacy, and their interactions as predictors, and age and gender as control variables (Model 1, Hayes 2013). Similar to previous studies, results revealed a main effect of eating self-efficacy: Those high in eating self-efficacy were more likely to choose a healthy snack, $\beta = -1.48$, SE = .31, Z = −4.74, $p < .001$. We observed two main effects of stimulus (human-as-machine vs. machine-only: $\beta = 8.67$, SE = 2.00, Z = 4.34, $p < .001$, and human-as-machine vs. human: $\beta = 9.40$, SE = 1.90, Z = 4.97, $p < .001$). Gender had a main effect (female participants, like in Study 1, chose healthier snacks, $\beta = -.69$, SE = .28, Z = −2.46, $p = .014$); age did not have an effect. More important, the model revealed two hypothesized Stimulus × Eating Self-efficacy interactions on snack choice, one between the human-as-machine and the machine-only conditions, $\beta = -1.64$, SE = .36, Z = −4.53, $p < .001$, and one between the human-as-machine and human conditions, $\beta = -1.76$, SE = .35, Z = −5.07, $p < .001$.

Further spotlight analyses on eating self-efficacy (M = 5.35, SD = 1.45) illustrated that among those with high eating self-efficacy (1 SD above the mean = 6.80), the effect of the human-as-machine stimulus was facilitative such that participants chose healthier snacks in the human-as-machine condition than in the machine-only condition, $\beta = -2.46$, SE = .60, $Z = -4.10$, $p < .001$, or in the human condition $\beta = -2.54$, SE = .61, $Z = -4.17$, $p < .001$.

In contrast, the human-as-machine stimulus again backfired among participants with low levels of eating self-efficacy (1 SD below the mean = 3.90), such that they chose unhealthier snacks after viewing the human-as-machine stimulus than in the machine-only condition, $\beta = 2.27$, SE = .66, $Z = 3.46$, $p = .001$, or the human condition $\beta = 2.53$, SE = .62, $Z = 4.13$, $p < .001$. The machine-only condition did not differ from the human condition for either group of consumers, indicating that a mere exposure to a machine (without any visual reference to humans) did not affect food choices.

Expectation and alternative accounts. We conducted the same analyses on expectation. The model revealed only a main effect of stimulus, such that all participants in the human-as-machine condition experienced a higher expectation to choose food in a cognitive, machine-like manner, compared to the machine-only condition, $\beta = 1.92$, SE = .74, $t = 2.61$, $p = .009$, and the human condition $\beta = 3.26$, SE = .61, $t = 5.30$, $p < .001$. The latter two conditions did not differ, suggesting that a mere exposure to a machine (without any visual reference to humans) did not affect participants' expectation to adopt a machine-like approach to food. There was no effect of eating self-efficacy nor interaction with stimuli.

We performed the same analyses on the alternative accounts (function of food, digestion capability, and hunger); these analyses revealed no differences between the three stimuli, eating self-efficacy, and no interaction effects (see full results in Web Appendix 6).

From stimulus to expectation to food choice. We proceeded to conduct a bias-corrected moderated mediation analysis (Model 15, Hayes 2013): The stimulus predicted the perceived expectation of adopting a machine-like approach to food, and individuals' eating self-efficacy moderated the effect of this expectation on food choice, with age and gender serving as control variables. Results without control variables again revealed consistent effects and are reported in Web Appendix 6 for completeness.

The results supported our predictions: The first part of the model showed that viewing the human-as-machine stimulus heightened the expectation to adopt a cognitive, machine-like approach to food compared to the machine-only condition: $\beta = 1.36$, SE = .17, t = 7.90, $p < .001$, and compared to the human condition: $\beta = 2.27$, SE = .17, t = 13.21, $p < .001$.

The second part of the model showed that for food choices, there were two direct effects of stimulus (human-as-machine vs. machine-only: $\beta = 6.37$, SE = 2.17, Z = 2.93, $p = .003$, and human-as-machine vs. human: $\beta = 4.59$, SE = 2.34, Z = 1.96, $p = .050$), and two interactions with eating self-efficacy, respectively ($\beta = -1.20$, SE = .39, Z = −3.07, $p = .002$; $\beta = -.86$, SE = .43, Z = −2.00, $p = .046$). Expectation also significantly affected food choices ($\beta = 1.98$, SE = .58, Z = 3.39, $p = .001$).

Importantly, whether expectation led to healthier or unhealthier choices depended on individuals' level of eating self-efficacy, as captured by a significant Expectation × Eating Self-efficacy interaction in the full model: $\beta = -.38$, SE = .11, Z = −3.54, $p < .001$. The conditional indirect effects for eating self-efficacy (M = 5.35, SD = 1.45) between the human-as-machine vs. machine-only conditions showed that a heightened expectation of adopting a machine-like approach to food led to healthier choices for those high in eating self-efficacy (1 SD above the mean = 6.80), $\beta = -.78$, 95% CI [−1.50 to −.29], but led to unhealthier choices for those low in eating self-efficacy (1 SD below the mean = 3.90), $\beta = .70$, SE = .36, 95% CI [.13 to 1.55]; index of moderated mediation ($\beta = -.51$, SE = .19, 95% CI [−.98 to −.29]). The same applied for the human-as-machine vs. human conditions: a heightened expectation led to healthier choices for those high in eating self-efficacy (1 SD above the mean = 6.80), $\beta = -1.29$, 95% CI [−2.49 to −.47], but unhealthier choices for those low in eating self-efficacy (1 SD below the mean = 3.90), β = 1.17, SE = .36, 95% CI [.20 to 2.59]; index of moderated mediation (β = −.85, SE = .19, 95% CI [−1.63 to −.38]).

We again conducted the same moderated mediation analyses with the alternative account variables (function of food, digestion capability, and hunger) as the mediator; there were no effects of stimulus on either of these variables, nor any significant (moderated) mediation effects (we report the results in Web Appendix 6).

In addition to these analyses, we also compared how long participants spent on writing about the stimulus they saw in each condition. A regression analysis with time spent on writing as the outcome variable, stimulus (human-as-machine vs. machine-only vs. human), eating self-efficacy, and their interaction as predictors, and age and gender as control variables (Model 1, Hayes 2013) revealed that there was no effect of stimulus, eating self-efficacy, or their interactions.

Employing a moderated mediation approach, we demonstrated that exposure to a human-as-machine stimulus led to a heightened expectation to adopt a cognitive, machine-like approach for all individuals, irrespective of their level of eating self-efficacy. The effect of expectation on food choice, however, was moderated by eating self-efficacy—it motivated those high in eating self-efficacy to make healthier choices but backfired among those low in eating self-efficacy. Priming machine alone did not lead to these effects, suggesting that consumers apply the expectation of making food choices in a cognitive, machine-like way to themselves only if the visual represented a human as a machine. Seeing a machine-only visual did not trigger an expectation for how humans should behave, just as seeing a human-only visual did not trigger expectations for how humans may need to behave differently. The observed effects also cannot be explained by altered food perceptions, hunger, or digestive capability.

Study 4: Triangulating the Role of Expectation Using Human-as-Machine Appearance Plus Movement Stimuli

Study 4 served to provide additional evidence on the proposed role of expectation (H2) and the divergent consequences it produces on food choices (H3) with yet another human-as-machine stimulus—altering human appearance and physical movement. Specifically, we used a virtual telepresence machine, which is gaining popularity in consumers' daily lives and in business interactions, to design our stimulus (see Web Appendix 3). As mentioned earlier, these types of technological advances will soon be used in the retail sector and restaurants (O'Reilly 2017), where food choices are often made. The chosen stimulus therefore has high relevance for practice and further expands the scope of our examination beyond the body's internal composition and face.

Furthermore, we focused on food-related alternative accounts in Study 3 but acknowledge that exposure to human-as-machine stimuli could alter one's level of emotionality or the perception of how competent humans in general are (vs. machines). We therefore wanted to measure and rule out these possibilities. Finally, to further enhance generalizability, we used another food choice in this study: yogurts that varied in calories, sugar, and fat.

Method

Participants. Three hundred three UK-based adults (67.0% female, $M_{age} = 38.26$) participated in the study through Prolific Academic. This study constituted a 2 (Stimulus: human-as-machine vs. human) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Stimulus design and pretest. In this study, we created a different human-as-machine stimulus by altering appearance and physical movement (Aggarwal and McGill 2012; Graham and Poulin-Dubois 1999; Morewedge, Preston, and Wegner 2007). In the human-as-machine condition, the appearance was illustrated as a robotic skeleton and a human face, just as seen in virtual telepresence machines; in the human condition, the appearance was illustrated in a regular human form (see Web Appendix 3; we included different genders to enhance generalizability). To incorporate the dimension of physical movement, we then showed participants a video clip of this person (either in a human-as-machine form or a human form) moving through an apartment for 45 seconds. In the human-as-machine condition, the movement was choppy/mechanistic; in the human condition, the movement was smooth/fluent (adopted from Tremoulet and Feldman 2000).

The pretest using the same two scales as in previous studies' pretests was successful. The human-as-machine stimulus was perceived as more machine-like than the human stimulus (see Web Appendix 3 for stimuli pretest details and results).

Procedure. Following the procedures in previous studies, participants first viewed one of the stimuli (human-as-machine or human, randomly assigned to a female or male version of the stimulus irrespective of their own gender), and watched the 45-second clip of this person moving through an apartment. Similar to the procedures in Study 2, participants were *not* asked to write 100 words about the stimuli, to further ensure that the observed effects could occur without mandatory reflection. Participants answered a filler question and then proceeded to enter their food choices.

Participants read a short introduction about a new yogurt company. They were told that the researchers had agreed to conduct a market study for this company to assess students' preferences for yogurts. They were then asked to choose one out of nine yogurts that they would like to receive and try. Yogurts differed in their level of healthiness, indicated by caloric, sugar, and fat content, ranging from 80 calories to 256 calories, with an increase of 22 calories between each choice and the next-higher-calorie choice (see Web Appendix 5 for the yogurt choices). To ensure that higher-calorie yogurts were indeed perceived as less healthy, we again conducted a posttest on the health perceptions of these yogurt options. As in prior studies, replacing calorie count with the health score from the posttest as the dependent measure revealed consistent results (see Web Appendix 5 for the posttest).

After selecting their choice of yogurt, participants were asked to report their perceived expectation of adopting a cognitive, machine-like approach to food as in Study 3 (Haslam 2006; Haslam et al. 2005; Cronbach's alpha = .71). While the stimuli in Study 3 did not specifically mention food or eating, they utilized digestive system visuals which could activate thoughts related to food. In this study, the human-as-machine stimulus was not related to digestive system, food, or eating, further underscoring that even digestion/food unrelated stimulus could activate an expectation about how *food choices* should be made. We also asked participants to respond to statements about their emotionality (Cronbach's alpha = .77) and perception of human competence (Cronbach's alpha = .59) to rule out these alternative accounts; see Appendix for full scales. All scales were presented in random order.

The survey ended with demographic information, the eating self-efficacy scale (Armitage and Connor 1999, Cronbach's alpha = .93), and suspicion probing as usual.

Results and Discussion

Food choice. None of the participants raised any suspicion or questions about the study. Yogurt choice (1 = *healthiest option* to 9 = *unhealthiest option*) was submitted as dependent variable to an analysis with stimulus (human-as-machine vs. human), eating self-efficacy (continuous measure), and their interaction as predictors, and age and gender as covariates (Model 1, Hayes 2013). Similar to prior studies, results revealed a main effect of eating self-efficacy: Those high in eating self-efficacy chose lower calorie yogurts, $\beta = -.42$, SE = .10, t = −4.27, $p < .001$. We again observed a main effect of stimulus (human-as-machine vs. human): $\beta = 2.68$, SE = .55, t = 4.86, $p < .001$. We also found a main effect of age, with older participants choosing healthier yogurts, $\beta = -.03$, t = −2.48, $p = .014$, and no gender effect. More important, the model again revealed the hypothesized Stimulus × Eating Self-efficacy interaction on yogurt choice, $\beta = -.49$, SE = .10, t = −5.00, *p < .001*.

Further spotlight analyses on eating self-efficacy (M = 5.39, SD = 1.42) illustrated that the effect of the human-as-machine stimulus was again facilitative among those with high eating self-efficacy (1 SD above the mean = 6.81): They chose healthier yogurts (M = 3.30) in the human-as-machine condition than in the human condition (M = 4.63, $\beta = -.67$, SE = .20, t = −3.38, *p* = .001). In contrast, the human-as-machine stimulus again backfired among participants with low levels of eating self-efficacy (1 SD below the mean = 3.97): They chose less healthy yogurts (M = 5.88) in the human-as-machine condition than in the human condition (M = 4.44, $\beta = .72$, SE = .14, t = 3.65, *p < .001*).

Expectation and alternative accounts. We conducted the same analyses on expectation as in Study 3. As hypothesized, we observed only a main effect of stimulus: participants in the human-as-machine condition experienced a higher expectation to choose food in a machine-like manner, compared to the human condition: $\beta = 1.40$, SE = .26, t = 5.32, *p < .001*. There was not an effect of eating self-efficacy nor interaction.

We again conducted the same analyses on the alternative accounts (emotionality, perceived human competence), which revealed no differences between the two stimuli, eating self-efficacy, or any interaction (we report the results in Web Appendix 6).

From stimulus to expectation to food choice. We proceeded to conduct a bias-corrected moderated mediation analysis (Model 15, Hayes 2013) as in Study 3. Results replicated the findings in Study 3: The first part of the model showed that viewing the human-as-machine stimulus heightened the expectation to adopt a cognitive, machine-like approach to food, $\beta = 1.28$, SE = .67, t = 19.17, *p < .001*, irrespective of age and gender. The second part of the model showed that for food choices, there was an effect of both eating self-efficacy ($\beta = -.76$, SE = .40, t = −1.93, p = .055) and of expectation ($\beta = 1.66$, SE = .54, t = 3.09, p = .002).

Most importantly, whether expectation led to healthier or unhealthier choices again depended on eating self-efficacy, as captured by a significant Expectation × Eating Self-efficacy interaction in the full model: $\beta = -.30$, SE = .10, t = −3.10, p = .002. The conditional indirect effects for eating self-efficacy (M = 5.39, SD = 1.42) again showed that a heightened expectation of adopting a machine-like approach to food led to significantly healthier choices for those high in eating self-efficacy (1 SD above the mean = 6.81), $\beta = -.50$, SE = .21, 95% CI [−.91 to −.06], but conversely led to unhealthier choices for those low in eating self-efficacy (1 SD below the mean = 3.97), $\beta = .59$, SE = .24, 95% CI [.01 to 1.09]; index of moderated mediation ($\beta = -.38$, SE = .13, 95% CI [−.64 to −.14]).

Conducting the same moderated mediation analyses with the alternative account variables (emotionality and perception of human competence) as the mediator revealed no effects of stimulus, nor any (moderated) mediation effects.

So far, we have documented across three types of stimuli (internal body composition, face, and appearance and movement), three types of food choices, and a diverse group of participants from different countries that human-as-machine representations led to healthier food choices for consumers high in eating self-efficacy but backfired for consumers low in eating self-efficacy. We also provided evidence that these divergent effects were driven by an activated expectation to choose food in a cognitive, machine-like manner, which resulted in divergent food choices. In a follow-up study (Web Appendix 9), we replicated the moderated mediation results in this study and further measured whether participants anticipated success or failure in meeting the activated expectation. The results verified that whereas participants high in eating self-efficacy anticipated success in meeting the expectation and thus chose healthier options, those low in eating self-efficacy anticipated failure in meeting the expectation, which led to the backfire effect.

The final study tested a theory-driven solution: If the backfire effect occurred because consumers low in eating self-efficacy found the expectation of adopting a cognitive, machine-like approach to food too difficult to meet, then by making consumers feel that they *can* meet this expectation, the backfire effect would be attenuated. Testing this possibility not only provides additional support for the role of expectation, but also offers a viable solution for marketers, educators, and policymakers; instead of withdrawing human-as-machine stimuli altogether or excluding specific consumer segments from these communications, interested parties can accompany a human-as-machine stimulus with an intervention message that makes everyone feel that they can meet the activated expectation.

Study 5: A Theory-Driven Intervention in the Field

In this study, we distributed flyers showing a human-as-machine representation (the digestive system stimulus used in Studies 1 and 3) to customers at a university-based cafeteria before they purchased lunch. Half of the flyers were accompanied by a message that aimed to make the activated expectation more doable, and half were not. This study further enhanced the external validity of our findings and its generalizability (from snack choices to lunch entrée choices), while testing a mechanism-driven solution.

Method

Intervention. We designed the intervention with the goal of making consumers, who are low in eating self-efficacy, believe that they can meet the expectation of adopting a cognitive, machine-like approach to food, without harming those high in eating self-efficacy. Specifically, in the intervention condition, an additional message stating “You CAN choose your food today with your head (not your heart)” was printed right under the human-as-machine visual; see Web Appendix 3 for the flyer. We informed participants that a head-based approach to food is easy and doable (instead of blatantly stating that a "cognitive" or "machine-like" approach is easy and doable) as this message is short, simple to process, and applicable for practical use. To ensure that adding this message indeed made the expectation activated by the human-as-machine stimulus seem more doable, we conducted a post-test. The post-test verified that when viewing the human-as-machine stimulus with the intervention message, participants indeed perceived it less difficult and more doable to meet the expectation of adopt a head-based, cognitive approach to food; see Web Appendix 3.

Procedure. In the field study, which took place from January 13 to February 7, 2020, at a university-based cafeteria, research assistants approached customers before they entered the cafeteria and inquired about their interest in participating in a study in exchange for $7.00 (see Web Appendix 3 for pictures of the study's set-up). Three hundred thirty-three customers (67.6% female, M_{age} = 41.07) participated. All customers were exposed to the human-as-machine stimulus (as the goal was to test the effectiveness of the intervention message); the study employed a 2 (Intervention: yes vs. no) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Customers who were willing to participate received a survey about a flyer. Under the cover story that the school was testing different flyers for effectiveness and wanted to make sure that the flyers stayed relevant to the customers and had good printing quality, all participating customers were asked to review a flyer and saw a flyer with a human-as-machine visual printed at the center (the digestive system stimulus used in Studies 1 and 3). The flyer either had an additional intervention message "You CAN choose your food today with your head (not your heart)" printed under the human-as-machine visual or not. The survey about the flyer included a few design-related questions (e.g., on color and clarity of the flyer), as well as questions on mood, hunger level, age, gender, and occupation/field of study. All customers listed the last three digits of their phone number and their initials (which served to link the surveys). Customers received \$2 for this survey and proceeded to buy their lunch at the cafeteria. This cafeteria offered a wide variety of entrée choices, including a salad and soup bar, international bowls, pizza, burgers, sandwiches, and a grill station.

Right after customers purchased lunch and paid, they were invited to participate in the second part of this study to receive another \$5, totaling \$7. All customers who took the first survey participated in the second part. Research assistants took a picture of the lunch that the customers had just purchased while the customers completed the second survey. The second survey included a few questions about the lunch purchased, the overall impression of the cafeteria, the two eating self-efficacy scales (Armitage and Connor 1999; Moorman and Matulich 1993), as well as phone number digits and initials to match their responses.

Results and Discussion

We asked two research assistants (blind to the hypotheses) to assess the healthiness of the lunch choices (1= *very healthy*, 5 = *not at all healthy*) based on the pictures. We averaged their scores (inter-coder reliability was high, $r = .72$, $p < .001$) and then conducted a regression analysis with stimulus (human-as-machine without intervention message vs. with intervention message), eating self-efficacy (Armitage and Connor 1999), and their interaction as predictors, and age and gender as control variables (Model 1, Hayes 2013). The model revealed a main effect of stimulus: $\beta = -2.05$, $SE = .39$, $t = -5.25$, $p < .001$. There was no direct effect of eating self-efficacy, age, or gender. More importantly, we found a significant Stimulus × Eating Self-efficacy interaction, $\beta = .31$, $SE = .07$, $t = 4.66$, $p < .001$.

Further spotlight analyses ($M = 5.78$, $SD = .94$) showed that the intervention helped consumers low in eating self-efficacy (1 SD below the mean = 4.84); they made healthier lunch choices when exposed to the human-as-machine stimulus with the intervention ($M = 2.24$) than without the intervention ($M = 3.33$), $\beta = -.55$, $SE = .09$, $t = -6.12$, $p < .001$. As expected, there was no effect of the message ($M_{no\ intervention}$ = 2.73 vs. $M_{intervention}$ = 2.81) among those high in eating self-efficacy (1 SD above the mean = 6.72), $\beta = .04$, $SE = .09$, $t = .44$, $p = .657$; they already felt that meeting the activated expectation was easy (see Figure 4).

Insert Figure 4 about here

We repeated these analyses with the alternative eating self-efficacy scale by Moorman and Matulich (1993), as tested in the two replications of Study 1 and in Study 2. The two eating self-efficacy scales were again correlated ($r(333) = .40$, $p < .001$), and results were consistent in both direction and significance (see Web Appendix 6).

Study 5 provided additional evidence for the proposed mechanism—that the divergent effects occurred because the consumers low (vs. high) in eating self-efficacy felt that it was difficult to meet the expectation of adopting a cognitive, machine-like approach to food. Most importantly, it also offers an effective solution for policymakers, educators, and marketers: By adding a message that makes a cognitive approach to food easier and more doable, the human-as-machine stimulus can lead to healthier choices for all consumers.

General Discussion

In an effort to fight obesity and educate consumers on how the human body functions, health marketing and education materials frequently portray humans as machines and encourage consumers to act more "machine-like," with slogans like "Fuel your body, not your emotions," or visuals that literally present humans as machines (see Web Appendix 1).

In this work, we put this belief to a test and used a variety of human-as-machine representations inspired by anthropomorphism research, health education, marketing practice, and recent technological advancements. We uncovered critical divergent effects of exposure to human-as-machine representations—it was facilitative for consumers high in eating self-efficacy but backfired among consumers low in eating self-efficacy (Studies 1–5). We further showed that this divergent effect happened because exposure to human-as-machine stimuli activated the expectation that one should adopt a cognitive, machine-like approach to food (Studies 3–4), which would be difficult to meet for consumers low in eating self-efficacy. Importantly, this backfire effect was alleviated when human-as-machine stimuli were accompanied with an intervention message that made consumers feel that they could meet the expectation of adopting a cognitive, head-based approach to food (Study 5).

Theoretical Contributions

Eating Self-efficacy. Our work echoes the growing interest in studying the push for a cognitive approach to food in consumer behavior research (Kozup, Creyer, and Burton 2003; Krishnamurthy and Prokopec 2010). We documented how using human-as-machine stimuli to promote this approach can create divergent effects on food choices, depending on consumers' chronic level of eating self-efficacy. Importantly, we further captured the underlying mechanisms accounting for these divergent responses: Exposure to human-as-machine stimuli activates an expectation to adopt a cognitive, machine-like approach to food; while this expectation is motivating to consumers high in eating self-efficacy, it backfires among those low in eating self-efficacy. Results of Studies 3–5 thus underscore the importance of this trait as the antecedent for how consumers would respond to an expectation about food consumption, subsequently resulting in expectation-aligned behaviors (Bandura and Cervone, 1983; Ozer and Bandura 1990).

Our work thus provides important insights and inspires future research regarding the rich psychologies of consumers of different levels of eating self-efficacy. While consumers high in eating self-efficacy already made healthier food choices than those low in eating self-efficacy (i.e., a significant main effect in Studies 1-4, directional in Study 5), consumers high in eating self-efficacy could still benefit from human-as-machine stimuli and make healthier choices (in all studies except for Study 2, in which eating self-efficacy was manipulated).

One possibility for the inconsistent results could be related to our eating self-efficacy manipulation. While the specific treatment used to manipulate eating self-efficacy in Study 2—social comparison—can be powerful and pervasive (Vartanian et al. 2015), the feeling that one is currently ahead of others can conversely license one to indulge (Huang, Lin, and Zhang 2019). If this occurs, it may cancel the originally positive effect of human-as-machine stimuli among these consumers. Future research is encouraged to explore how balancing/ licensing may interact with eating self-efficacy perceptions to affect food choices.

Another possibility could be that the manipulation of high eating self-efficacy did not induce sufficiently high self-perception on eating self-efficacy. In the original scale development (Armitage and Connor 1999), the sample mean of eating self-efficacy was 4.53 (SD = 1.45); more recent research using this measure (Naughton, McCarthy, and McCarthy 2016) found a sample mean of 5.22 (SD = .89). A close examination of the means in all our studies using this scale (from 5.35 to 5.78) revealed an aggregate mean of 5.25 (SD = 1.35), which was consistent with prior literature. However, the manipulation check of the high eating self-efficacy condition in Study 2 only produced a mean of 5.01 (see Table 1). We further conducted a meta-analysis aggregating the eating self-efficacy scores across all studies that used this efficacy scale and had a continuous food-choice dependent variable (i.e., Studies 1, 2, 4, and follow-up); the threshold analysis of this aggregate dataset revealed that the human-as-machine (vs. human) stimuli backfired for consumers with eating self-efficacy scores between 1.00 and 5.37, and were facilitative for consumers with eating self-efficacy scores between 6.07 to 7.00. Hence, the high eating self-efficacy condition in Study 2 may not be sufficiently high to produce a significant, positive effect. We encourage future research to explore other ways to shift people's perception of eating self-efficacy.

Insert Table 1 about here

For consumers low in eating self-efficacy, prior research has shown that these consumers have difficulties with eating rationally, unemotionally, and analytically (Clark et al. 1991; Costanzo et al. 2001; Glynn and Ruderman 1986; Knäuper 2013; Stotland, Zuroff, and Roy 1991; Toray and Cooley 1997; Wilson-Barlow, Hollins, and Clopton 2014). Our work suggests that these past experiences could lead consumers low in eating self-efficacy to act against human-as-machine stimuli and the expectation of adopting a cognitive, machine-like approach to food. Importantly, by adding an intervention message that made the expectation seem easier to meet (Study 5), we were able to attenuate the previously observed backfire effect. This field study not only provides a relevant solution for practitioners but also complements work on the importance of setting achievable expectations in inducing health-related behavioral change (Bandura 1991; Klesse et al. 2012).

We chose to focus on eating self-efficacy as it is one of the most frequently used constructs in health behavior theories (Glanz and Bishop 2010). Still, future research should explore the robustness of these effects using other related constructs, such as health behavioral control (Droms and Craciun 2014), eating self-control (Dzhogleva and Lamberton 2014; Haws, Davis, and Dholakia 2016), emotional eating (van Strien et al. 1986), and overall self-regulation (Vohs and Heatherton 2000). Lastly, we note that consumers' past and current fitness levels, health conditions, and whether or not they are on a diet affect how they perceive their eating self-efficacy; while we did not measure these habits and physical conditions in our studies, we encourage future research to take these variables into consideration when studying eating self-efficacy and healthy eating.

Anthropomorphism and Dehumanization. This research introduces the concept of mechanistic dehumanization—visually representing humans as machines—to the consumer behavior literature as a reverse process of anthropomorphism (Aggarwal and McGill 2007; Epley, Waytz, and Cacioppo 2007). Our findings echo those in anthropomorphism research that demonstrate that changes along the human–machine continuum prompt specific behavioral expectations (Aggarwal and McGill 2012; Kim and Kramer 2015; Kim and McGill 2011). We found that when humans are portrayed as machines, it activates an expectation that one should behave in a machine-like way.

For dehumanization research, our work expands prior studies on dehumanization to underscore its relevance for consumer behavior research in three ways. First, while prior work in dehumanization has focused primarily on how changes in facial features and movements influence how humans are perceived on the human–machine continuum (Deska, Almaraz, and Hugenberg 2017; Deska, Lloyd, and Hugenberg 2018; Hugenberg et al. 2016; Looser and Wheatley 2010), our work tested other dimensions such as altering internal body composition and appearance. Our findings offer a rich set of stimuli for future work on dehumanization and marketing, while bringing dehumanization literature closer to consumers' everyday lives. Second, we explored an important downstream consequence that is highly relevant for consumers and marketing, and underscored how human-as-machine stimuli could activate unique expectations in the context of food, leading to both positive and negative effects on choices that consumers make in their everyday lives. Third, we shed light on the importance of idiosyncratic differences. While previous research promotes the idea that feeling like a human is desirable and valuable for all individuals (Goldenberg et al. 2001; Haslam et al. 2005), we found that dehumanization stimuli can generate divergent effects.

Importantly, the direction of changes along the human–machine continuum warrants further investigation. When encountering a stimulus, individuals first make a binary choice to classify a stimulus as either a "human" or "nonhuman" (Mathur and Reichling 2016). Based on this first-level assessment, they generate expectations (e.g., dehumanized humans should be more rational, anthropomorphized machines more emotional). In all our studies, we informed participants that they were evaluating a human (body, face, physical movements).

As a result, our stimuli depict humans portrayed as machines. However, the line between humans and machines becomes blurrier, and many physical features convey conflicting signals (Ferrey, Burleigh, and Fenske 2015; Gray, Gray, and Wegner 2007). Future research should investigate the boundary at which a human or a machine is categorized as such, and explore other dehumanization types. Examples include marketing messages with mechanical voices, as well as artificial intelligence software that blurs the line between humans and machines (Luo et al. 2020; Puntoni et al. 2020).

Furthermore, the impact of human-as-machine representations on other types of food decisions as well as decisions in other domains should be examined. We focused on food choices (snack choices in Studies 1–4 and lunch purchases in Study 5) because of the relevance of human-as-machine representations in this context and the importance of uncovering unintended risks in this domain, but we believe that the documented effects and mechanisms could occur in other domains (e.g., financial, medical, and social decisions).

Lastly, demographic and cultural differences should be further considered. Age and gender affect how people feel about machines (Bartneck et al. 2007; Nomura, Kanda, and Suzuki 2006) and how they make food choices (Ares and Gámbaro 2007). In our studies, we did not find consistent effects of these variables. While this could result from the natural variance in our samples (i.e., students vs. Prolific Academic population), we believe that future research is warranted. The same speculation applies to different cultures, which vary in the expectations they hold about machines (e.g., Asian vs. Western cultures, Kaplan 2004; Kitano 2006). Culture also affects specific food-related expectations. While we showed that exposure to human-as-machine representations did not change whether food was construed as a source of energy or pleasure among participants from Western culture (Study 3), it is possible that the observed effects would differ in cultures that associate food with pleasure

(Rozin et al. 1999), or in contexts in which a cognitive, machine-like approach to food is not expected (i.e., buying a gift for someone, or bringing food/snacks to a social gathering).

Practical Implications

Important non-academic stakeholder groups will find value in this research. Many stakeholders encourage consumers to make food choices in a cognitive (and less emotional) manner to battle the rise of obesity. We used stimuli available in the real world (digestive system illustrations used in health marketing, face morphing available in mobile apps, and teleconferencing agents used in business meetings and retail) and showed that while consumers indeed felt expected to adopt a more cognitive, machine-like approach to food, this expectation can backfire. Our results thus ring a cautionary bell for nonprofit organizations, policy makers, educators, and for-profit health marketers: A strategy used with good intentions of educating consumers and improving their health can have an unintended dark side that hurts a vulnerable segment of consumers. Our work thus echoes the insights from prior research, such that 1) confronting consumers with expectations on how they should behave can be risky if it is not aligned with their abilities, and 2) influencers should carefully tailor their content for target audiences (e.g., Pechmann and Catlin 2016).

There is hope, though, as the backfire effect documented in this research can be attenuated by altering the perception of one's relative level of eating self-efficacy (Study 2) and by reassuring consumers that meeting the expectation to make cognitive, head-based food choices is doable (Study 5). Our research thus provides practical solutions to help circumvent the backfire effect for various stakeholders who plan to use human-as-machine stimuli to encourage healthy eating. Lastly, understanding the potential processes that cause indulgent food choices is also crucial for consumers, especially as human-as-machine stimuli become more prevalent in the lives of consumers around the world.

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FIGURES

FIGURE 1
OVERVIEW OF THE MODEL AND HYPOTHESES

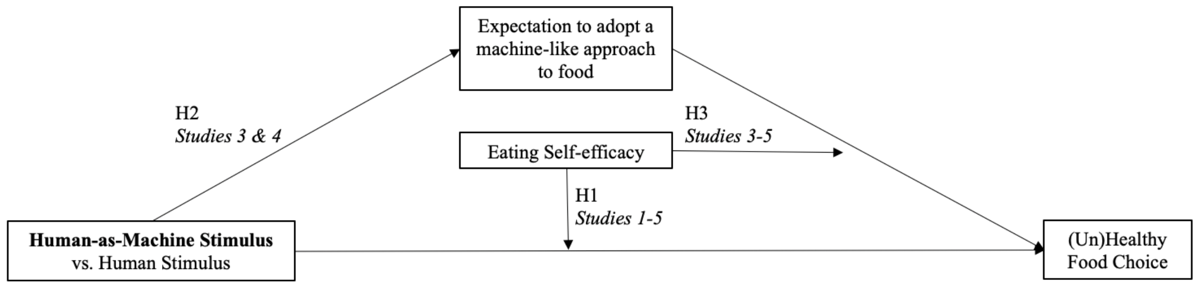


FIGURE 2
THE EFFECT OF STIMULUS ON SNACK CHOICES FOR CONSUMERS LOW VS. HIGH IN EATING SELF-EFFICACY– MEASURED (STUDY 1)

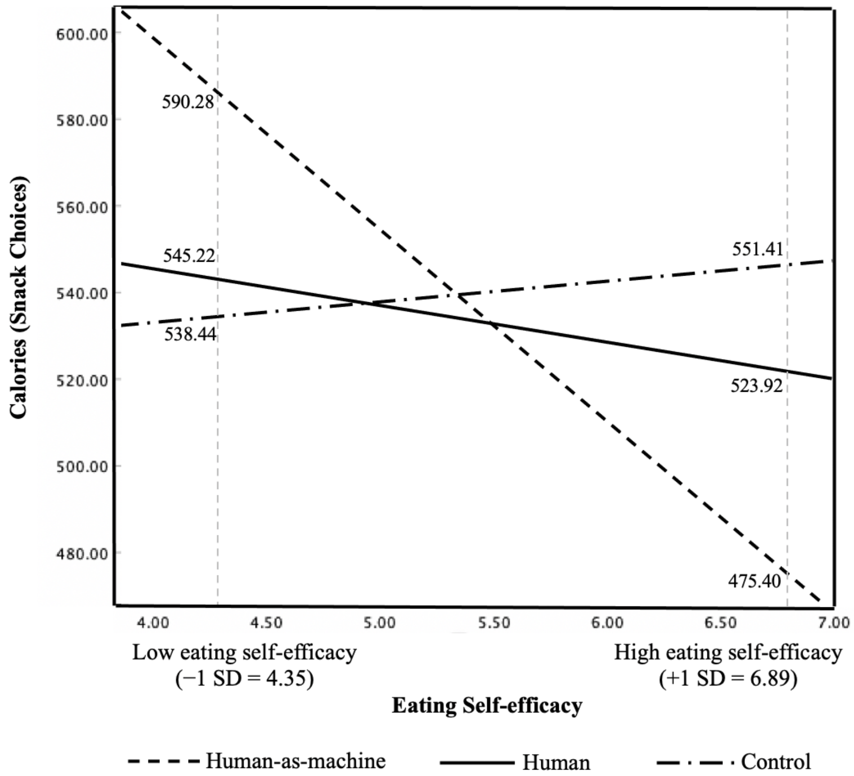


FIGURE 3
THE EFFECT OF STIMULUS ON SNACK CHOICES FOR CONSUMERS LOW VS. HIGH IN EATING SELF-EFFICACY – MANIPULATED (STUDY 2)

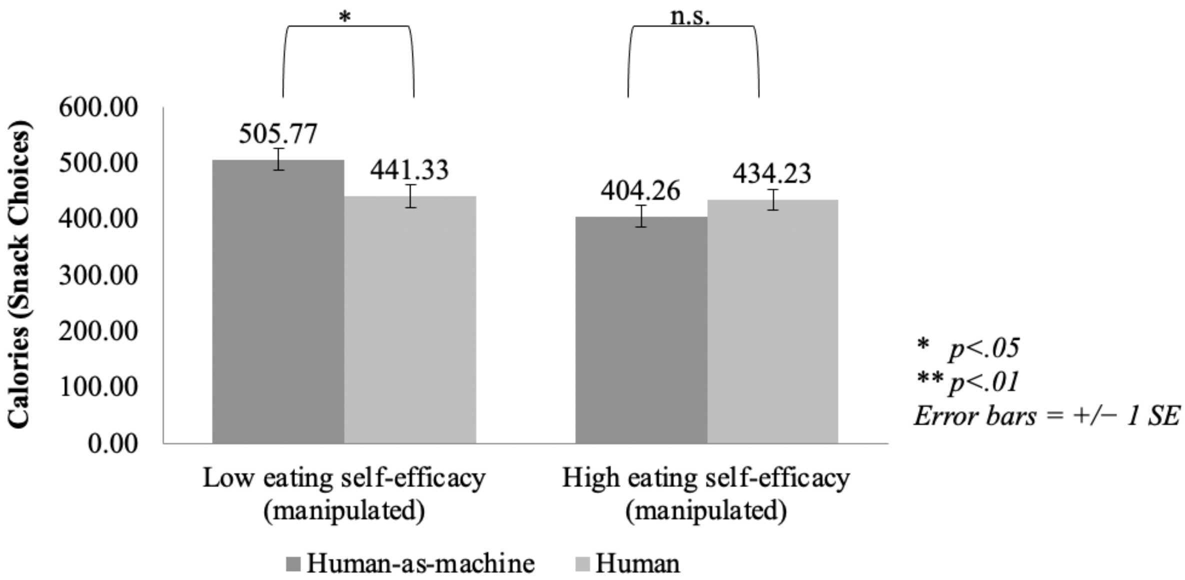
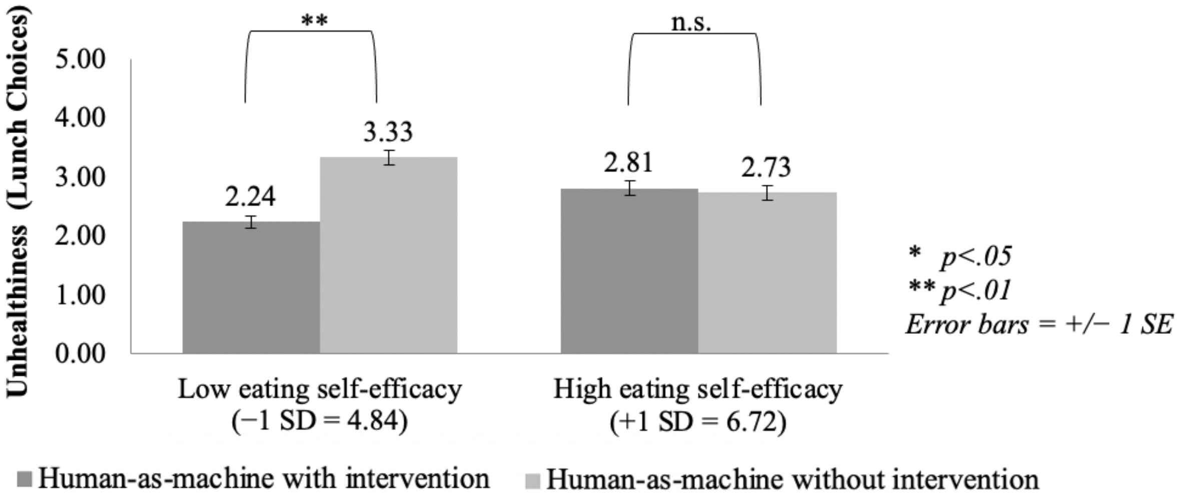


FIGURE 4
THE EFFECT OF STIMULUS AND INTERVENTION MESSAGE ON LUNCH CHOICE
(STUDY 5)



TABLES

TABLE 1
REGIONS OF SIGNIFICANCE FOR THE EFFECT OF STIMULUS ON FOOD CHOICE FOR DIFFERENT LEVELS OF EATING SELF-EFFICACY

Study	Sample	Eating Self-efficacy (SE) Scale	Dependent Variable	Eating SE (- 1 SD)	Eating SE (Mean)	Eating SE (+1 SD)	Johnson Neyman regions of significance	Comments
Study 1	Prolific Academic (UK)	Armitage and Connor 1999	Calories Snacks	4.35	5.62	6.89	1.00 to 4.11 and 6.74 to 7.00	
Study 1 - Replication 1	Crowdflower (US)	Moorman and Matulich 1993	Calories Snacks	2.85	4.05	5.25	1.00 to 3.10 and 5.20 to 7.00	
Study 1 - Replication 2	MTurk (US)	Moorman and Matulich 1993	Calories Snacks	2.82	4.12	5.42	1.00 to 3.24 and 5.10 to 7.00	
Study 2	Undergraduate students (Netherlands)	Armitage and Connor 1999	Calories Snacks	4.71		5.01	n.a.	**Eating self-efficacy was manipulated, scores reflect the manipulation check*
Study 3	Undergraduate students (Netherlands)	Armitage and Connor 1999	Snack Choice	3.90	5.35	6.80	1.00 to 4.92 and 5.76 to 7.00	** Snack choices were binary (healthy/unhealthy)*
Study 4	Prolific Academic (UK)	Armitage and Connor 1999	Yogurt Choice	3.30	5.39	6.81	1.00 to 4.84 and 6.06 to 7.00	
Study 4 - Follow-up	Prolific Academic (UK)	Armitage and Connor 1999	Yogurt Choice	4.05	5.45	6.85	1.00 to 5.35 and 6.23 to 7.00	
Study 5	Customers university cafeteria (US)	Armitage and Connor 1999 Moorman and Matulich 1993	Lunch Choice	4.84	5.78	6.72	n.a.	**Study did not include a human condition*

APPENDIX

Eating Self-efficacy (Armitage and Connor 1999)
The following statements are related to your lifestyle and your behavior concerning your health. Please state to what extent you agree with the following statements.

1. I believe I have the ability to eat a healthy diet in the next month (1 = *definitely do not*, 7 = *definitely do*).
2. To what extent do you see yourself as being capable of eating a healthy diet in the next month? (1 = *very unlikely*, 7 = *very likely*).
3. How confident are you that you will be able to eat a healthy diet in the next month? (1 = *very unsure*, 7 = *very sure*).
4. If it were entirely up to me, I am confident that I would be able to eat a healthy diet in the next month. (1 = *strongly disagree*, 7 = *strongly agree*).

(Note: We replaced "low fat" with "healthy" diet for the purpose of this research.)

Eating Self-efficacy (adopted from Moorman and Matulich 1993)*
It's easy to cut back on snacks and treats. (1 = *strongly disagree*, 7 = *strongly agree)*
It's easy to eat fresh fruits and vegetables regularly.
I find it hard to moderate my red meat consumption. (r)
It's easy to minimize the additives I consume.
It's easy for me to reduce my sodium intake.

** These five items from the original scale assessed participants' eating self-efficacy (other items pertained to general health behaviors and thus were not included to create the composite measure)*

Scales – Food-Related Alternative Accounts (Study 3)

Function of Food (Cramer and Antonides 2011)
The main function of food is (1 = *provide pleasure/fun*, 7 = *satisfy hunger*).

It is important that food…
1. …has a good taste. (1 = *strongly disagree*, 7 = *strongly agree*)
2. …has a pleasant appearance. (1 = *strongly disagree*, 7 = *strongly agree*)
3. …provides energy. (1 = *strongly disagree*, 7 = *strongly agree*)
4. …improves one's performance. (1 = *strongly disagree*, 7 = *strongly agree*)

Digestion Capability (1 = *strongly disagree*, 7 = *strongly agree*)
1. I feel that my body can easily digest the food I consume.
2. I feel that my body is prepared to digest a variety of food items easily.
3. I feel that my body has no problem digesting what I choose to eat.

Hunger: How hungry do you feel at the moment? (1 = *not at all*, 7 = *very much*)

Scales – Other Alternative Accounts (Study 4)

Emotionality (1 = *not at all*, 7 = *very much*)

1. How emotional did you feel when you looked at this image?
2. How emotional did you feel when you made your food choice?
3. How much was your food choice based on emotions/feelings?

Human Competence (1 = *not at all*, 7 = *very much*)

1. How competent are humans in general?
2. How competent are humans in making good food choice

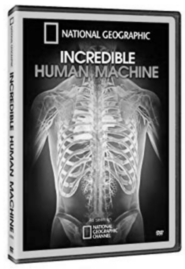
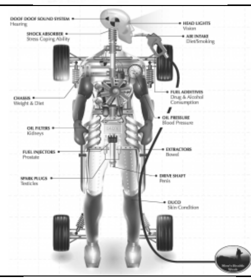
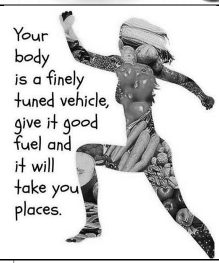
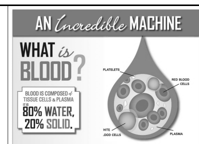
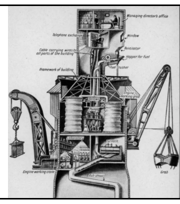
Portraying Humans as Machines to Promote Health:

Unintended Risks, Mechanisms, and Solutions

Web Appendix

SECTION ONE

Examples of Human-as-Machine Representations in Health Campaigns and Food Marketing

Health Campaigns (NGO & Public Policy)		
Human as Machine to Promote Health		
National Geographic	The Incredible Human Machine – Unhealthy behavior as "error" in the system	
Men's Health Week	The human body as car – Drugs and alcohol hurt the "engine"	
GBCHealth	Your body is a finely tuned vehicle – Give it good fuel and it will take you places	
American Heart Association	The human heart as machine – Healthy blood as fuel	
Centers for Disease Control and Prevention (CDC)	The human body as a machine – Some parts cannot be replaced	
COSI – Center of Science and Industry	Keep the body engines in tip-top shape by keeping the body healthy	
Singularity Hub	If the body is a machine, can it be maintained indefinitely?	

Marketing Campaigns (For-Profit Companies)		
Human as Machine to Promote Health		
Centrum	Vitamin supplements to power the human machine	
Weetabix Limited	Weetabix cereals – Healthy fuel for the human machine	
Red Bull	Consuming a Red Bull makes you analytical and rational like a human machine	 https://www.youtube.com/watch?v=7KpFfilSYqY
Human as Human (Not Machine) to Promote Indulgence		
Mars Incorporated	You become human again once you consume a Snickers bar	
Nestlé	You become human again once you consume a Kit Kat bar	
Anheuser-Busch	Superbowl ad: Drinking Michelob Ultra beer – The "human" thing to do	 https://www.youtube.com/watch?v=nNfv9wsttKE
Heineken	You are re-humanized after consuming a glass of Heineken	 https://www.youtube.com/watch?v=l-NfrBgYIEQ

SECTION TWO

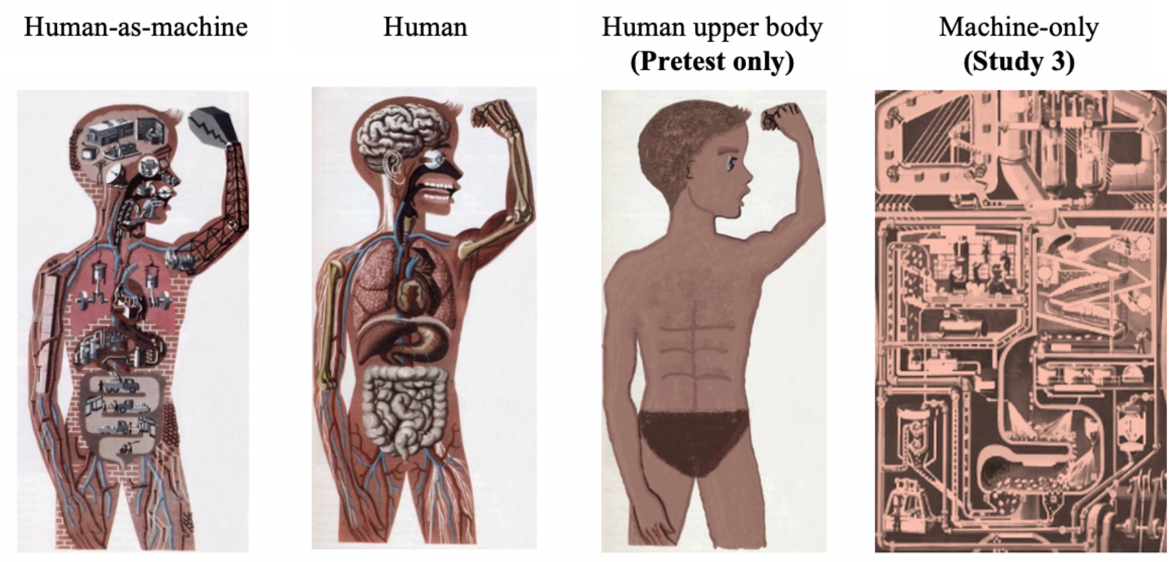
Pilot Test – Adopting a Cognitive, Machine-like Approach to Food for Consumers High (vs. Low) in Eating Self-efficacy

To verify that people high (vs. low) in eating self-efficacy would indeed feel that they have (vs. do not have) the ability to make food choices in a cognitive, machine-like manner, we conducted a pilot test. We asked 301 UK-based participants on Prolific Academic (66.8% female, $M_{age} = 35.82$) to report their perceived ability of adopting a cognitive, machine-like approach to food on three 7-point Likert scales (Haslam 2006; Haslam et al. 2005; 1 = *strongly disagree*, 7 = *strongly agree*; Cronbach's alpha = .62): "I feel that I have the ability to make my food choices . . . unemotional, analytical, cold." They also answered two sets of scales to gauge their chronic level of eating self-efficacy (one adopted from the diet self-efficacy scales by Armitage and Connor 1999, Cronbach's alpha = .92; the other adopted from health behavioral control scales by Moorman and Matulich 1993, Cronbach's alpha = .70; both scales were adjusted to be eating-specific, see Appendix for the full scales).

A simple linear regression model ($F(3,297) = 6.18$, $p < .001$) with age and gender as covariates showed that a higher level of eating self-efficacy was related to a higher perceived ability to approach food choices in a cognitive, machine-like manner for both sets of eating self-efficacy scales (Armitage and Connor 1999 scale: $\beta = .16$, $t = 3.35$, $p = .001$, 95% CI [.067; to 258]; Moorman and Matulich 1993 scale: $\beta = .19$, $t = 3.36$, $p = .001$, 95% CI [.080 to .307]). Results were consistent in both direction and significance without covariates.

SECTION THREE

Internal Body Composition Stimuli (Studies 1 and 3)



Pretest: We recruited 99 UK-based participants (70.7% female, Mage = 36.59) from Prolific Academic and measured human versus machine perception using scales from the anthropomorphism literature (Aggarwal and McGill 2007; Kim and McGill 2017; Romero and Craig 2017). Participants were randomly assigned to view one of the three images and rate it on three 7-point Likert scales: "The human (body) . . . 1 = *looks like a machine*, 7 = *looks like a human*; 1 = *does not look alive at all*, 7 = *looks very alive*; 1 = *contains mainly machine-like features*, 7 = *contains mainly human-like features*." We created a composite measure of machine–human perception by averaging participants' responses to these three items (Cronbach's alpha = .59). For comprehensiveness, we also included classic measures of dehumanization: "The human (body) is represented as . . . unemotional, cold, rigid, fungible (lacking individuality), superficial, passive, inert (lifeless)"; 1 = *strongly disagree*, 7 = *strongly agree* (Haslam, 2006; Cronbach's alpha = .84).

The results verified that the digestive system presented as a machine was indeed perceived as more machine-like on the human–machine continuum ($M = 3.54$, $SD = 1.81$) than the digestive system presented as human organs ($M = 5.18$, $SD = 1.24$; $t(64) = 5.51$, $p < .001$, $d = 1.36$) and the human upper-body condition ($M = 5.08$, $SD = 1.41$; $t(64) = 4.82$, $p < .001$, $d = 1.19$); the latter two groups did not differ ($t(64) = .31$, $p = .759$, $d = .08$). Results were similar for the reverse-coded dehumanization scale: the digestive system presented as a machine was perceived as more machine-like ($M = 3.20$, $SD = .98$) than the digestive system presented as human organs ($M = 3.87$, $SD = 1.00$; $t(64) = 2.76$, $p = .007$, $d = .07$) and the human upper-body condition ($M = 3.77$, $SD = 1.27$; $t(64) = 2.05$, $p = .045$, $d = .50$); the latter two groups did not differ ($t(64) = .37$, $p = .713$, $d = .10$). For both scales, results for each individual item were consistent with the composite measure. The scales were positively correlated ($r(99) = .40$, $p < .001$).

Face Stimuli (Study 2)

Pretest: Using the same procedures as the pretest in Study 1, for this pretest we recruited 100 UK-based participants (67.0% female, $M_{age} = 36.24$) on Prolific Academic. Participants were randomly assigned to one of two conditions. In the human-as-machine condition, participants saw a human face with machine-like features. In the human condition, participants viewed the same human face without machine-like features. In both conditions, we randomly assigned participants to a male or female face. After viewing the stimulus, participants evaluated the face on the same three items of the machine–human perception scale (Aggarwal and McGill 2007; Kim and McGill 2017; Romero and Craig 2017; Cronbach's alpha = .90) and the same seven items of the dehumanization scale (Haslam 2006; Cronbach's alpha = .85) as in Study 1's pretest.

The pretest was successful. Participants who saw the human-as-machine face evaluated the face as more machine-like (M = 4.27, SD = 1.54) than those who saw the human face (M = 5.70, SD = 1.53; $t(98) = 4.67$, $p < .001$, d = .94). They also evaluated the human-as-machine face as more dehumanized (M = 3.52, SD = 1.08) on the reverse-coded dehumanization scale than those who saw the human face (M = 4.01, SD = 1.10; $t(98) = 2.24$, $p = .027$, d = .45). The scales were again positively correlated ($r(100) = .52$, $p < .001$).

Appearance and Physical Movement Stimuli (Study 4)

Pretest: Using the same procedures, we recruited 102 UK-based participants (62.7% female, M_{age} = 34.68) from Prolific Academic for this pretest. Participants were randomly assigned to view one of the stimuli and evaluated the stimulus on the same three items of the machine–human perception scale (Aggarwal and McGill 2007; Kim and McGill 2017; Romero and Craig 2017; Cronbach's alpha = .97) and the same seven items of the dehumanization scale (Haslam, 2006; Cronbach's alpha = .95).

The pretest verified that the human-as-machine stimulus was perceived as more machine-like (M = 1.71, SD = 1.38) than the human stimulus (M = 6.25, SD = 1.41; t(100) = 16.46, $p < .001$, d = 3.27). It was also perceived as more dehumanized (M = 2.64, SD = 1.19) than the human stimulus (M = 5.17, SD = 1.03; t(100) = 11.51, $p < .001$, d = 2.29). The two scales were again correlated (r(102) = .78, $p < .001$).

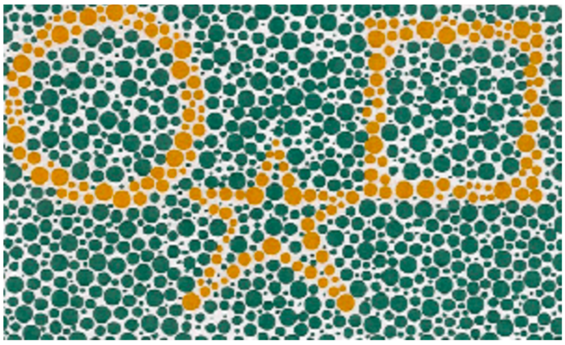
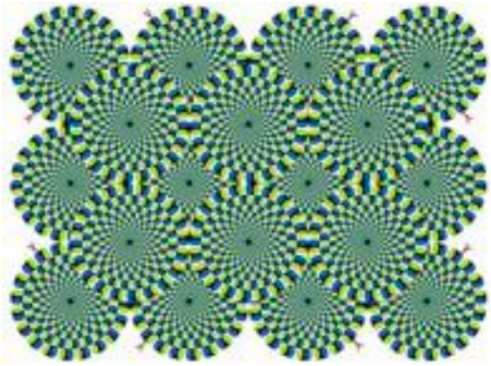
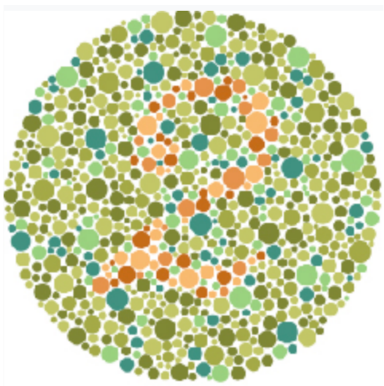
Intervention Stimuli (Study 5)

Post-test: To gauge whether the intervention message made consumers feel that meeting an expectation of adopting a cognitive, machine-like approach to food was easier and more doable, we conducted a post-test with 101 participants (66.3% female, $M_{age} = 36.02$) from Prolific Academic. Participants were asked to evaluate different public policy materials and were randomly given a flyer with or without the intervention message. Afterwards, they answered six statements: "I feel that meeting the expectation to make food choices 1) unemotionally, 2) analytically, 3) in a cold-tempered manner is [1 = difficult; 7 = easy] and [1 = not doable; 7 = doable]. Results of the independent t-test verified that participants who were exposed to the flyer with the intervention message felt that meeting the expectation of adopting a cognitive, machine-like approach to food was easier and more doable ($M = 4.77$, $SD = 1.15$) than those exposed to the flyer without the intervention message ($M = 4.03$, $SD = 1.00$), $t(99) = 3.47$, $p = .001$, $d = .67$.

Field Study Set-up (Study 5)

SECTION FOUR

Filler Questions

	What shapes do you see in this image (mark all that apply)? o Circle o Triangle o Square o Heart
	Did you perceive the image to move? o Yes o No
	Which colors do you see in this image (mark all that apply)? o Yellow o Blue o Pink o Red o Orange
	Do you see a number in this image? o Yes o No

SECTION FIVE

Snack Choice (Studies 1 and 2)

# of ingredients	19
calories	250 cal
weight	53 g

# of ingredients	19
calories	210 cal
weight	35 g

# of ingredients	8
calories	110 cal
weight	28 g

# of ingredients	19
calories	80 cal
weight	170 g

# of ingredients	1
calories	30 cal
weight	90 g

# of ingredients	12
calories	160 cal
weight	49 g

# of ingredients	2
calories	80 cal
weight	136 g

# of ingredients	33
calories	210 cal
weight	50 g

# of ingredients	18
calories	240 cal
weight	60 g

# of ingredients	24
calories	170 cal
weight	28 g

* Results of a posttest (n = 107, 67.3% female, $M_{age} = 27.05$) on the health perception of these 10 items verified that these items were indeed perceived as increasingly unhealthy as their caloric content increased, $F(1, 106) = 1720.41$, $p < .001$, $\eta^2 = .942$. Item-to-item analyses on health perception were also significant and consistent with the analysis across all 10 items.

Snack Choice (Study 3)

* Results of the posttest (n = 107, 67.3% female, M_{age} = 27.05) verified that the health perception between the two healthy snacks (energy bar, M = 4.46, and yogurt, M = 4.26) was not significantly different, $F(1, 106) = 1.51$, $p = .222$, nor was it significantly different between the two unhealthy snacks (chocolate bar, M = 1.60, and chips, M = 1.67), $F(1, 106) = .69$, $p = .407$; as expected, a significant difference was found between these two types of snacks (healthy vs. unhealthy), $F(1, 106) = 338.25$, $p < .001$, $\eta^2 = .761$. We included two healthy and two unhealthy snacks (instead of one of each) to minimize the influence of participants' personal preference (loving or hating a specific snack).

Yogurt Choice (Study 4)

* Results of the posttest (n = 107, 67.3% female, M_{age} = 27.05) on the health perception of these yogurt options verified that they were indeed perceived as increasingly unhealthy as their caloric content increased, $F(1, 106) = 68.16$, $p < .001$, $\eta^2 = .391$. Item-to-item analyses on health perception were also significant and consistent with the analysis across all nine items.

SECTION SIX

Overview of Results without Age and Gender Covariates

Study 1

Regression Model 1, Hayes 2013 -> DV: Calories of Snack Choices

X1 - Human-as-machine vs. Control:	$\beta = 274.47$, SE = 72.17, t = 3.80, *p < .001*
X2 - Human-as-machine vs. Human:	$\beta = 202.81$, SE = 81.85, t = 2.48, *p* = .014
Eating self-efficacy:	$\beta = -46.28$, SE = 8.88, t = −5.21, *p < .001*
X1 x Eating self-efficacy:	$\beta = -51.26$, SE = 12.67, t = −4.04, *p < .001*
X2 x Eating self-efficacy:	$\beta = -36.96$, SE = 13.95, t = −2.65, *p* = .009

Spotlight Analysis

Human-as-machine vs. Control

Low eating self-efficacy (4.35): M = 590.28, M = 538.51; $\beta = 51.77$, SE = 22.68, t = 2.28, *p* = .023

High eating self-efficacy (6.89): M = 472.71, M = 551.15; $\beta = -78.44$, SE = 24.07, t = −3.26, *p* = .001

Human-as-machine vs. Human

Low eating self-efficacy (4.35): M = 590.28, M = 548.06; $\beta = 45.05$, SE = 25.54, t = 1.76, *p* = .079

High eating self-efficacy (6.89): M = 472.71, M = 524.39; $\beta = -51.67$, SE = 23.14, t = −2.23, *p* = .026

Study 2

ANOVA -> DV: Calories of Snack Choices

Stimulus (Human-as-machine vs. Human):	F(1, 192) = .79, *p* = .376
Eating self-efficacy:	F(1, 192) = 7.82, *p* = .006
Stimulus x Eating self-efficacy:	F(1, 192) = 5.91, *p* = .016

Study 3

Regression Model 1, Hayes 2013 -> DV: Snack Choice (0=healthy; 1=unhealthy)

X1 - Human-as-machine vs. Machine-only:	$\beta = 7.80$, SE = 1.91, Z = 4.08, *p < .001*
X2 - Human-as-machine vs. Human:	$\beta = 8.90$, SE = 1.83, Z = 4.86, *p < .001*
Eating self-efficacy:	$\beta = -1.42$, SE = .30, Z = −4.71, *p < .001*
X1 x Eating self-efficacy:	$\beta = -1.48$, SE = .35, Z = −4.30, *p < .001*
X2 x Eating self-efficacy:	$\beta = -1.65$, SE = .33, Z = −4.95, *p < .001*

Regression Model 1, Hayes 2013 -> DV: Expectation to Adopt a Machine-like Approach

X1 - Human-as-machine vs. Machine-only:	$\beta = 1.93$, SE = .46, t = 6.85, *p < .001*
X2 - Human-as-machine vs. Human:	$\beta = 3.25$, SE = .72, t = 2.66, *p* = .008
Eating self-efficacy:	$\beta = .03$, SE = .08, t = .30, *p* = .764
X1 x Eating self-efficacy:	$\beta = .10$, SE = .13, t = .79, *p* = .429
X2 x Eating self-efficacy:	$\beta = .19$, SE = 11.95, t = 1.73, *p* = .185

Moderated Mediation Model 15, Hayes 2013

Outcome Variable: Expectation to Adopt a Machine-like Approach

X1 - Human-as-machine vs. Machine-only:	$\beta = 1.36$, SE = .17, t = 7.91, *p < .001*
X2 - Human-as-machine vs. Human:	$\beta = 2.27$, SE = .17, t = 13.24, *p < .001*

Outcome Variable: Snack Choice

X1 - Human-as-machine vs. Machine-only:	$\beta = 5.48$, SE = 2.05, Z = 32.67, *p* = .008
X2 - Human-as-machine vs. Human:	$\beta = 4.37$, SE = 2.24, Z = 1.96 *p* = .051
Expectation:	$\beta = 1.81$, SE = .56, Z = 3.20, *p* = .001
Eating self-efficacy:	$\beta = -.21$, SE = .55, Z = .38, *p* = .705
X1 x Eating self-efficacy:	$\beta = -1.05$, SE = .37, Z = −2.83, *p* = .005
X2 x Eating self-efficacy:	$\beta = -.81$, SE = .41, Z = −1.97, *p* = .050
Expectation x Eating self-efficacy:	$\beta = -.34$, SE = .10, Z = −3.35, *p* = .001

Conditional Indirect Effects
Human-as-machine vs. Machine-only
Low eating self-efficacy (3.90): β =.63, SE = .34, 95% CI [.08 to 1.45]
High eating self-efficacy (6.80): β = −.71, SE = .31, 95% CI [−1.59 to .27]

Human-as-machine vs. Human:
Low eating self-efficacy (3.90): β = 1.06, SE = .57, 95% CI [.13 to 2.48]
High eating self-efficacy (6.80): β = −1.19, SE = .51, 95% CI [−2.66 to −.44]

Results for Alternative Account Variables

Function of Food (Hedonic vs. Utilitarian)			
Regression Model 1, Hayes 2013 -> DV: Function of Food			
With covariates/control variables		*Without covariates/control variables*	
X1	β = −.07, SE = .85, t = −.09 *p* = .930	X1	β = −.40, SE = .85, t = −.46 *p* = .643
X2	β = −.66, SE = .71 t = −.92, *p* = .357	X2	β = −.75, SE = .72, t = −1.05, *p* = .296
Eating SE	β = .11, SE = .10, t = 1.16, *p* = .248	Eating SE	β = .11, SE = .10, t = 1.14, *p* = .255
X1xEating SE	β = .03, SE = .15, t = .17, *p* = .863	X1xEating SE	β = .08, SE = .15, t = .60, *p* = .593
X2xEating SE	β = .14, SE =.13, t = 1.04, *p* = .300	X2xEating SE	β = .16, SE = .13, t = 1.20, *p* = .231
Gender	β = .40, SE = .17, t = −2.39, *p* = .017		
Age	β = −.00, SE = .05, t = −.10 *p* = .919		
Moderated Mediation Model 15, Hayes 2013			
With covariates/control variables		*Without covariates/control variables*	
Function of Food			
X1	β = .05, SE = .20, t = −.23 *p* = .815	X1	β = −.03, SE = .20, t = −.15, *p* = .877
X2	β = .07, SE = .20, t = −.34, *p* = .736	X2	β = −.08, SE = .20, t = −.42, *p* = .673
Gender	β = .39, SE = .16, t = 2.35, *p* = .020		
Age	β = −.00, SE = .05, t = −.04, *p* = .970		
Healthiness of Snack Choice (0=healthy; 1=unhealthy)			
X1	β =8.55, SE = 2.01, Z = 4.28, *p* <.001	X1	β = 7.74, SE = 1.92, Z = 4.02, *p* <.001
X2	β = 9.36, SE = 1.91, Z = 4.90, *p* <.001	X2	β = 8.87, SE = 1.84, Z = 4.82, *p < .001*
Function	β =-.61, SE = .45, Z = -1.37, *p* = .172	Function	β = -.49, SE = .44, Z = -1.13, *p* = .260
Eating SE	β = -1.84, SE = .40, Z = -4.56, *p < .001*	Eating SE	β = -1.74, SE = .39, Z = -4.48, *p < .001*
X1xEating SE	β = -1.63, SE = .36, Z = -4.47, *p < .001*	X1xEating SE	β = -.1.48, SE = .35, Z = -4.25, *p < .001*
X2xEating SE	β = -1.75, SE = .35, Z = -5.01, *p < .001*	X2xEating SE	β = -.1.66, SE = .34, Z = -4.92, *p < .001*
FuncxEatingSE	β = .11, SE = .08, Z = 1.49, *p* = .137	FuncxEatingSE	β = .10, SE = .08, Z = .1.31, *p* = .189
Gender	β = .71, SE = .28, Z = 2.50, *p* = .012		
Age	β = −.01, SE = .08, Z = -.18, *p* = .856		

Digestion Capacity			
Regression Model 1, Hayes 2013 -> DV: Digestion Capacity			
With covariates/control variables		*Without covariates/control variables*	
X1	β = .55, SE = .71, t = .77, *p* = .439	X1	β = .97, SE = .72, t = 1.34, *p* = .180
X2	β = −.13, SE = .60, t = −.23, *p* = .821	X2	β = .00, SE = .61, t = .01, *p* = .991
Eating SE	β = .02, SE = .08, t = .25, *p* = .807	Eating SE	β = .02, SE = .08, t = .22, *p* = .827
X1xEating SE	β = −.10, SE = .13, t = -.81, *p* = .418	X1xEating SE	β = −.17, SE = .13, t = −1.34, *p* = .180
X2xEating SE	β = .03, SE = .10, t = .27, *p* = .790	X2xEating SE	β = −.00, SE = .11, t = −.04, *p* = .971
Gender	β = -.57, SE = .14, t = -4.04, *p < .001*		
Age	β = -.05, SE = .04, t = -1.17, *p* = .243		
Moderated Mediation Model 15, Hayes 2013			
With covariates/control variables		*Without covariates/control variables*	
Digestion Capacity			
X1	β = −.02, SE = .16, t = −.14, *p* = .886	X1	β = .00, SE = .17, t = .04, *p* = .968
X2	β = .02, SE = .16, t = .13, *p* = .900	X2	β = −.00, SE = .17, t = −.05, *p* = .958
Gender	β = −.60, SE = .14, t = −4.36, *p < .001*		
Age	β = −.04, SE = .04, t = −1.11, *p* = .267		

Healthiness of Snack Choice(0=healthy; 1=unhealthy)			
X1	β = 8.60, SE = 1.99, Z = 4.33, *p*<.001	X1	β =7.91, SE = 1.91, Z = 4.14, *p* <.001
X2	β = 9.34, SE = 1.88, Z = 4.97, *p*<.001	X2	β =8.94, SE = 1.83, Z = 4.90, *p* <.001
Digestion	β = .24, SE = .50, Z = .54, *p* = .591	Digestion	β = .22, SE = .45, Z = .49, *p* = .626
Eating SE	β = -1.04, SE = .54, Z = -1.94, *p* = .053	Eating SE	β = -.97, SE = .53, Z =-1.84, *p* = .066
X1xEating SE	β = -1.64, SE = .36, Z = -4.55, *p < .001*	X1xEating SE	β = -1.51, SE = .34, Z = -4.38, *p < .001*
X2xEating SE	β = -1.75, SE = .35, Z = -5.08, *p < .001*	X2xEating SE	β = -1.67, SE = .33, Z = -5.00, *p < .001*
DigxEatingSE	β = -.08, SE = .08, Z = -.95, *p* = .344	DigxEatingSE	β = -.08, SE = .08, Z = -1.01, *p* = .312
Gender	β = .57, SE = .29, Z = 2.00, *p* = .046		
Age	β = .04, SE = .08, Z = .44, *p* = .663		

Hunger			
Regression Model 1, Hayes 2013 -> DV: Hunger			
With covariates/control variables		*Without covariates/control variables*	
X1	β = .53, SE = 1.12, t = .47, *p* = .637	X1	β = 1.09, SE = 1.12, t = .97, *p* = .331
X2	β = −1.21, SE = .93, t = −1.30, *p* = .195	X2	β = −1.05, SE = .94, t = −1.12 *p* = .270
Eating SE	β = -.10, SE = .13, t = -.79, *p* = .428	Eating SE	β = -.10, SE = .13, t = -.77, *p* = .439
X1xEating SE	β = −.08, SE = .19, t = −.40, *p* = .693	X1xEating SE	β = −.17, SE = .20, t = −.88, *p* = .382
X2xEating SE	β = .22, SE = .17, t = 1.27, *p* = .204	X2xEating SE	β = .18, SE = .17, t = 1.03, *p* = .303
Gender	β = -.72, SE = .22, t = -3.25, *p* = .001		
Age	β = .00, SE = .06, t = .03, *p* = .979		
Moderated Mediation Model 15, Hayes 2013			
With covariates/control variables		*Without covariates/control variables*	
Hunger			
X1	β = .12, SE = .26, t = .45, *p* = .655	X1	β = .14, SE = .26, t = .54, *p* = .589
X2	β = −.14, SE = .26, t = −.52, *p* = .599	X2	β = −.17, SE = .26, t = −.63, *p* = .528
Gender	β = -.65, SE = .22, t = -2.98, *p* = .003		
Age	β = .00, SE = .06, t = .05, *p* = .960		
Healthiness of Snack Choice			
X1	β =8.90, SE = 2.01, Z = 4.42, *p*< .001	X1	β =7.90, SE = 1.92, Z = 4.10, *p* <.001
X2	β = 9.68, SE = 1.91, Z = 5.06, *p*<.001	X2	β = 9.00, SE = 1.84, Z =4.89, *p* <.001
Hunger	β = -.28, SE = .30, Z = -.94, *p* = .349	Hunger	β = -.30, SE = .29, Z = -1.03, *p* = .302
Eating SE	β = -1.77, SE = .38, Z = -4.65, *p < .001*	Eating SE	β = -1.68, SE = .36, Z = -4.60, *p < .001*
X1xEating SE	β = -1.68, SE = .36, Z = -4.61, *p < .001*	X1xEating SE	β = -1.50, SE = .35, Z = -4.33, *p < .001*
X2xEating SE	β = -1.82, SE = .35, Z = -5.17, *p < .001*	X2xEating SE	β = -1.68, SE = .34, Z = -5.00, *p < .001*
HungxEatingSE	β = .08, SE = .05, Z = 1.43, *p* = .152	HungxEatingSE	β = .07, SE = .05, Z = 1.39, *p* = .164
Gender	β = .81, SE = .30, Z = 2.80, *p* = .5005		
Age	β = -.01, SE = .08, Z = -.15, *p* = .884		

Study 4

Regression Model 1, Hayes 2013 -> DV: Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)

X - Human-as-machine vs. Human: β = 2.79, SE = .55, t = 5.03, *p < .001*
Eating self-efficacy: β = −.46, SE = .10, t = −4.58, *p < .001*
X x Eating self-efficacy: β = −.51, SE = .10, t = −5.13, *p < .001*

Regression Model 1, Hayes 2013 -> DV: Expectation to Adopt a Machine-like Approach

X - Human-as-machine vs. Human: β = 1.39, SE = .26, t = 5.31, *p < .001*
Eating self-efficacy: β = .04, SE = .05, t = .76, *p* = .450
X x Eating self-efficacy: β = .02, SE = .05, t = .45, *p* = .655

Moderated Mediation Model 15, Hayes 2013

Outcome Variable: Expectation to Adopt a Machine-like Approach
Human-as-machine vs. Human: β = 1.28, SE = .07, t = 19.20, *p < .001*

Outcome Variable: Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)
X - Human-as-machine vs. Human: β = .17, SE = .10, t = .17, *p* = .863
Expectation: β = 1.69, SE = .54, t = 3.12, *p* = .002
Eating self-efficacy: β = −.76, SE = .40, t = −1.90, *p* = .057

X x Eating self-efficacy: $\beta = -.03$, SE = .18, $t = -.19$, $p = .852$
Expectation x Eating self-efficacy: $\beta = -.31$, SE = .10, $t = -3.16$, $p = .002$

Conditional Indirect Effects
Human-as-machine vs. Human
Low eating self-efficacy (3.97): $\beta = .59$, SE = .25, 95% CI [.12 to 1.10]
High eating self-efficacy (6.81): $\beta = -.52$, SE = .22, 95% CI [−.96 to −.08]

Results for Alternative Account Variables

Emotionality			
Regression Model 1, Hayes 2013 -> DV: Emotionality			
With covariates/control variables		*Without covariates/control variables*	
X	$\beta = -.34$, SE = .28, $t = -1.24$, $p = .217$	X	$\beta = -.35$, SE = .28, $t = -1.27$, $p = .204$
Eating SE	$\beta = -.01$, SE = .05, $t = -.29$, $p = .769$	Eating SE	$\beta = -.01$, SE = .05, $t = -.22$, $p = .825$
XxEating SE	$\beta = .05$, SE = .05, $t = 1.02$, $p = .307$	XxEating SE	$\beta = .05$, SE = .05, $t = 1.05$, $p = .293$
Gender	$\beta = -.12$, SE = .14, $t = -.84$, $p = .402$		
Age	$\beta = .00$, SE = .00, $t = .51$, $p = .609$		
Moderated Mediation Model 15, Hayes 2013			
With covariates/control variables		*Without covariates/control variables*	
Emotionality			
X	$\beta = -.07$, SE = .07, $t = -.98$, $p = .329$	X	$\beta = -.07$, SE = .07, $t = -.32$, $p < .001$
Gender	$\beta = -.12$, SE = .14, $t = -.82$, $p = .411$		
Age	$\beta = .00$, SE = .00, $t = .56$, $p = .575$		
Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)			
X	$\beta = 2.62$, SE = .55, $t = 4.73$, $p < .001$	X	$\beta = 2.72$, SE = .56, $t = .87$, $p < .001$
Emotionality	$\beta = -.27$, SE = .48, $t = -.56$, $p = .577$	Emotionality	$\beta = -.43$, SE = .48, $t = -.90$, $p = .368$
Eating SE	$\beta = -.49$, SE = .22, $t = -2.26$, $p = .025$	Eating SE	$\beta = -.58$, SE = .21, $t = -2.72$, $p = .007$
XxEating SE	$\beta = -.48$, SE = .10, $t = -4.87$, $p < .001$	XxEating SE	$\beta = -.50$, SE = .10, $t = -5.00$, $p < .001$
EmoxEating SE	$\beta = .03$, SE = .09, $t = .32$, $p = .750$	EmoxEating SE	$\beta = .06$, SE = .09 $t = .67$, $p = .504$
Gender	$\beta = -.37$, SE = .29, $t = -1.28$, $p = .202$		
Age	$\beta = -.03$, SE = .01, $t = -2.42$, $p = .016$		

Human Competence			
Regression Model 1, Hayes 2013 -> DV: Human Competence			
With covariates/control variables		*Without covariates/control variables*	
X	$\beta = .11$, SE = .24, $t = .47$, $p = .636$	X	$\beta = .11$, SE = .24, $t = .44$, $p = .660$
Eating SE	$\beta = .08$, SE = .04, $t = 1.90$, $p = .586$	Eating SE	$\beta = .09$, SE = .04, $t = 1.99$, $p = .475$
XxEating SE	$\beta = -.03$, SE = .04, $t = -.66$, $p = .509$	XxEating SE	$\beta = -.03$, SE = .04, $t = -.63$, $p = .529$
Gender	$\beta = -.02$, SE = .12, $t = -.16$, $p = .873$		
Age	$\beta = .00$, SE = .00, $t = .51$, $p = .610$		
Moderated Mediation Model 15, Hayes 2013			
Human Competence			
X	$\beta = -.04$, SE = .06, $t = -.65$, $p = .517$	X	$\beta = -.04$, SE = .06, $t = -.67$, $p = .501$
Gender	$\beta = -.02$, SE = .13, $t = -.18$, $p = .861$		
Age	$\beta = .00$, SE = .00, $t = .72$, $p = .471$		
Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)			
X	$\beta = 2.70$, SE = .55, $t = 4.87$, $p < .001$	X	$\beta = 2.80$, SE = .56, $t = 5.04$, $p < .001$
Competence	$\beta = -.26$, SE = .58, $t = -.45$, $p = .652$	Competence	$\beta = -.30$, SE = .58, $t = -.48$, $p = .631$
Eating SE	$\beta = -.51$, SE = .45, $t = -1.13$, $p = .260$	Eating SE	$\beta = -.58$, SE = .45, $t = -1.21$, $p = .230$
XxEating SE	$\beta = -.49$, SE = .10, $t = -4.99$, $p < .001$	XxEating SE	$\beta = -.51$, SE = .10, $t = -5.15$, $p < .001$
CompxEatingSE	$\beta = .02$, SE = .10, $t = .22$, $p = .827$	CompxEatingSE	$\beta = .02$, SE = .10, $t = .24$, $p = .813$
Gender	$\beta = -.37$, SE = .28, $t = -1.30$, $p = .196$		
Age	$\beta = -.03$, SE = .01, $t = -2.45$, $p = .015$		

Study 5

Eating Self-efficacy Scale (Armitage and Connor 1999)

Regression Model 1, Hayes 2013 -> DV: Healthiness of Lunch Choice (1=healthy; 5=unhealthy), without control variables

X – No Intervention vs. Intervention	$\beta = -1.93$, SE = .38, t = −5.02, *p < .001*
Eating self-efficacy:	$\beta = .02$, SE = .07 t = .24, *p* = .808
X x Eating self-efficacy:	$\beta = .30$, SE = .07, t = 4.46, *p < .001*

Spotlight Analysis

No Intervention vs. Intervention
Low eating self-efficacy (4.84): M = 3.71, M = 2.69; $\beta = -.51$, SE = .09, t = −5.86, *p < .001*
High eating self-efficacy (6.72): M = 3.19, M = 3.27; $\beta = .040$, SE = .09, t = .45, *p* = .652

Eating Self-efficacy Scale (Moorman and Matulich 1993)

Regression Model 1, Hayes 2013 -> DV: Healthiness of Lunch Choice (1=healthy; 5=unhealthy), with control variables

X – No Intervention vs. Intervention	$\beta = -.87$, SE = .29, t = −3.05, *p* = .003
Eating self-efficacy:	$\beta = .05$, SE = .06 t = .83, *p* = .406
X x Eating self-efficacy:	$\beta = .13$, SE = .06, t = 2.21, *p* = .028
Age	$\beta = -.00$, SE = .00, t = −18, *p* = .855
Gender	$\beta = -.10$, SE = .13, t = −76, *p* = .449

Spotlight Analysis

No Intervention vs. Intervention
Low eating self-efficacy (3.76): M = 3.56, M = 2.76; $\beta = -.51$, SE = .09, t = −5.86, *p < .001*
High eating self-efficacy (6.03): M = 3.16, M = 3.38; $\beta = .040$, SE = .09, t = .45, *p* = .652

Regression Model 1, Hayes 2013 -> DV: Healthiness of Lunch Choice (1=healthy; 5=unhealthy), without control variables

X – No Intervention vs. Intervention	$\beta = -.83$, SE = .28, t = −2.96 *p* = .003
Eating self-efficacy:	$\beta = .04$, SE = .06 t = .71, *p* = .475
X x Eating self-efficacy:	$\beta = .12$, SE = .06, t = 2.16, *p* = .031

Spotlight Analysis

No Intervention vs. Intervention
Low eating self-efficacy (3.76): M = 3.54, M = 2.79; $\beta = -.38$, SE = .09, t = −4.20, *p < .001*
High eating self-efficacy (6.03): M = 3.36, M = 3.15; $\beta = .10$, SE = .09, t = 1.15, *p* = .253

SECTION SEVEN

Replications with a Different Eating Self-efficacy Scale
and a Reversed Order of Measurement

Replication 1

Method

Participants. Two hundred forty-five US-based adults (62.4% female, $M_{age} = 37.68$) recruited from Crowdflower participated in this study. The study used a 3 (Stimulus: human-as-machine vs. human vs. control) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Procedure. The procedure was similar to Study 1. Participants saw different representations of the human body (digestive system presented as a machine vs. as human organs), or the control stimulus (a map) and wrote 100 words about the stimuli (Gino, Kouchaki, and Galinsky 2015; Smith et al. 2008), and then were asked to choose three snack items (each in a $3 portion size) out of a selection of 10. Participants then proceeded to another set of two filler questions. Before exiting the study, participants entered demographic information and reported any suspicion or question they might have about the survey. They also answered questions regarding their health behavioral control (Moorman and Matulich 1993). Of this 12-item scale, five items directly assessed participants' eating self-efficacy and thus constituted our key composite measure of interest (Cronbach's alpha = .74; see Appendix for the scale). Using the full health behavioral control scale revealed consistent results. All participants were debriefed, allowed to comment on the study, and entered into the lottery to receive $9 cash (the monetary value of the coupons).

Results and Discussion

Following the same analysis procedures as in Study 1, we conducted a regression analysis with stimulus (human-as-machine vs. human vs. control), eating self-efficacy (continuous measure), and their interaction as predictors, with age and gender serving as control variables (Model 1, Hayes 2013).

The model revealed a main effect of eating self-efficacy ($\beta = -57.83$, SE = 11.02, $t = -5.26$, $p < .001$); people with higher eating self-efficacy chose lower-calorie snacks. The model also revealed two main effects of stimulus (human-as-machine condition vs. control condition: $\beta = 185.02$, SE = 68.84, $t = 2.69$, $p = .008$ and human-as-machine condition vs. human condition: $\beta = 191.11$, SE = 67.84, $t = 2.81$, $p = .005$). We also found a main effect of age, $\beta = -2.37$, SE = .65, $t = -3.62$, $p < .001$; older participants chose lower-calorie snacks. There was no gender effect. More important, we found two significant Stimulus × Eating Self-efficacy interactions, one between the human-as-machine and the control condition, $\beta = -44.40$, $t = -2.78$, $p = .006$, and the other between the human-as-machine and the human condition, $\beta = -47.15$, $t = -2.89$, $p = .004$.

Further spotlight analyses on eating self-efficacy (M = 4.05, SD = 1.20) illustrated that those with high eating self-efficacy (1 SD above the mean = 5.25) chose lower-calorie snacks in the human-as-machine condition (M = 435.01) than in the control condition (M = 483.01), $\beta = -48.00$, SE = 26.47, $t = -1.81$, $p = .071$, or the human condition (M = 491.34), $\beta = -56.33$, SE = 28.72, $t = -1.96$, $p = .051$; the human and control conditions did not differ.

Among those with low eating self-efficacy (1 SD below the mean = 2.85), the effect of the human-as-machine stimulus was reversed, such that participants chose higher-calorie snacks after viewing the human-as-machine stimulus (M = 573.57 calories) than the control stimulus (M = 515.18), β = 58.39, SE = 28.21, t = 2.07, *p* = .040, or the human stimulus (M = 516.93), β = 56.64, SE = 27.07, t = 2.09, *p* = .037; the human and control conditions did not differ.

Results without Covariates

Regression Model 1, Hayes 2013 -> DV: Calories of Snack Choices

X1 - Human-as-machine vs. Control:	β = 210.32, SE = 70.33, t = 2.99, *p* = .003
X2 - Human-as-machine vs. Human:	β = 190.96, SE = 69.67, t = 2.74, *p* = .007
Eating self-efficacy:	β = −64.33, SE = 11.17, t = −5.76, *p < .001*
X1 x Eating self-efficacy:	β = −51.63, SE = 16.30, t = −3.17, *p* = .002
X2 x Eating self-efficacy:	β = −50.17, SE = 16.73, t = −3.00, *p* = .003

Spotlight Analysis

Human-as-machine vs. Control
Low eating self-efficacy (2.85): M = 574.92, M = 512.03; β = 62.89, SE = 28.88, t = 2.18, *p* = .030
High eating self-efficacy (5.25): M = 421.06, M = 481.66; β = −60.60, SE = 26.91, t = −2.25, *p* = .025

Human-as-machine vs. Human
Low eating self-efficacy (2.85): M = 574.92, M = 527.20; β = 47.71, SE = 27.65, t = 1.73, *p* = .085
High eating self-efficacy (5.25): M = 421.06, M = 493.32; β = −72.30, SE = 29.22, t = −2.47, *p* = .014

Replication 2

Method

Participants. Two hundred twenty-seven US-based participants (38.8% female, M_{age} = 35.50) from Amazon MTurk participated in this study. The study used a 3 (Stimulus: human-as-machine vs. human vs. control) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Procedure. The procedure was the same as Replication 1, except that we used a reversed order of measurement: We measured people's chronic level of eating self-efficacy (Cronbach's alpha = .80) first, inserted filler survey questions, and then exposed them to the stimuli (human-as-machine vs. human vs. control). We then inserted another filler survey, and then captured participants' food choices using the same incentive-aligned choice.

Results and Discussion

We found results consistent with Replication 1 and Study 1: Higher levels of eating self-efficacy again led to lower calorie choices, β = −34.95, SE = 10.10, t = −3.46, *p* = .001. We again observed two main effects of stimulus (human-as-machine condition vs. control condition: β = 189.40, SE = 66.64, t = 2.84, *p* = .005 and human-as-machine condition vs. human condition: β = 220.98, SE = 67.54, t = 3.27, *p* = .001). More important, we replicated two significant Stimulus × Eating Self-efficacy interactions, one between the human-as-machine condition and the control condition, β = −45.42, SE = 15.46, t = −2.94, *p* = .004, and the other between the human-as-machine condition and the human condition, β = −53.92, SE = 15.57, t = −3.46, *p* = .001.

Results from the spotlight analysis on eating self-efficacy (M = 4.12 , SD = 1.30) were consistent as well: Participants with high eating self-efficacy (1 SD above the mean = 5.42) chose lower-calorie snacks in the human-as-machine condition (M = 439.69) than in the control condition (M = 496.25), β = −56.56, SE = 28.61, t = −1.98, *p* = .049, or the human condition (M = 510.61), β = −70.92, SE = 28.81, t = −2.46, *p* = .015; the human and control conditions did not differ. Among those with low eating self-efficacy (1 SD below the mean = 2.82), the effect of the human-as-machine stimulus was again reversed, such that participants chose higher-calorie snacks after viewing the human-as-machine stimulus (M = 530.46) than after viewing either the control stimulus (M = 469.02), β = 61.44, SE = 28.40, t = 2.16, *p* = .032, or the human stimulus (M = 461.34), β = 69.12, SE = 29.09, t = 2.38, *p* = .018; the human and control conditions did not differ.

Results without Covariates

Regression Model 1, Hayes 2013 -> DV: Calories of Snack Choices

X1 - Human-as-machine vs. Control:	β = 185.89, SE = 66.61, t = 2.79, *p* = .006
X2 - Human-as-machine vs. Human:	β = 215.87, SE = 67.31, t = 3.21, *p* = .002
Eating self-efficacy:	β = −34.53, SE = 10.10, t = −3.42, *p* = .001
X1 x Eating self-efficacy:	β = −44.96, SE = 15.46, t = −2.91, *p* = .004
X2 x Eating self-efficacy:	β = −53.68, SE = 15.56, t = −3.45, *p* = .001

Spotlight Analysis

Human-as-machine vs. Control
Low eating self-efficacy (2.82): M = 528.06, M = 468.81; β = 59.24, SE = 28.38, t = 2.08, *p* = .038
High eating self-efficacy (5.42): M = 438.37, M = 495.91; β = −57.54, SE = 28.61, t = −2.01, *p* = .046

Human-as-machine vs. Human
Low eating self-efficacy (2.82): M = 528.06, M = 463.38; β = 64.67, SE = 28.79, t = 2.25, *p* = .026
High eating self-efficacy (5.42): M = 438.37, M = 513.12; β = −74.74, SE = 28.68, t = −2.61, *p* = .010

SECTION EIGHT

Manipulation of Eating Self-efficacy and Manipulation Checks (Study 2)

What is your height in cm?
What is your weight in kg?

How many of your meals in an average week include red meat?

1 or less meals	2-3 meals	4-6 meals	7-9 meals	10 meals or more
○	○	○	○	○

How many of your weekly meals are high in sodium (because they are canned, packaged, restaurant prepared or take-out options)?

1 or less meals	2-3 meals	4-6 meals	7-9 meals	10 meals or more
○	○	○	○	○

How many of your weekly meals are high in additives* (because they are labelled diet/sugar-free, are processed, or frozen)?

1 or less meals	2-3 meals	4-6 meals	7-9 meals	10 meals or more
○	○	○	○	○

How many unhealthy snacks do you eat in an average week?

2 or less snacks	3-5 snacks	6-10 snacks	10-13 snacks	14 snack or more (two or more per day)
○	○	○	○	○

How many servings of fruits and vegetables do you eat in an average week?

16 or more servings	12-15 servings	8-11 servings	4-7 servings	3 or less servings
○	○	○	○	○

High Eating Self-efficacy Feedback

According to your score, you are classified as "very capable" to follow a healthy eating life style: You are in the highest quartile of the total student distribution in this study. Overall, you possess great ability to regulate sodium intake, monitor or reduce meat consumption and snacking, and consume sufficient amount of fruits and vegetables. Therefore, your odds of succeeding in eating healthily are very high at this moment.

Low Eating Self-efficacy Feedback

According to your score, you are classified as "having difficulties" in following a healthy eating life style: You are in the lowest quartile of the total student distribution in this study. Overall, you are struggling to regulate sodium intake, monitor or reduce meat consumption and snacking, and consume sufficient amount of fruits and vegetables. Therefore, your odds of succeeding in eating healthily are very low at this moment.

Manipulation checks: An independent-sample t-test for eating self-efficacy (Armitage and Connor 1999) verified that participants reported significantly lower eating self-efficacy in the low eating self-efficacy condition (M = 4.71, SD = 1.08), compared to those in the high self-efficacy condition (M = 5.01, SD = 1.05), t(194) = 2.01, p = .046, d = .29. Results were consistent with the second eating self-efficacy scale (Moorman and Matulich 1993): $M_{\text{low eating self-efficacy}}$ = 5.29, SD = 1.43 vs. $M_{\text{high eating self-efficacy}}$ = 5.73, SD = 1.10, t(194) = 2.41, p = .017, d = .34. We also conducted a separate pretest for the manipulation; the results were successful and consistent with the manipulation checks in the study.

SECTION NINE

Follow-Up Study on Expectation and Anticipated Success/Failure

Method

Participants. Five hundred eighty-four UK-based adults (67.8% female, $M_{age} = 33.12$) participated in the study though Prolific Academic. This study constituted a 2 (Stimulus: human-as-machine vs. human) × Eating Self-efficacy (measured as a continuous variable) between-subjects design.

Procedure. The procedure was similar to Study 4, except that in addition to expectation items, participants further answered statements about their anticipation of success and failure: "Should I attempt to make my food choices…unemotional, analytical, cold, *I will feel* 1) like a success, 2) content, 3) satisfied" (Bandura and Cervone 1983, Cronbach's alpha = .58). Other items included emotions such as empowerment and encouragement (Rawlett 2014, Warren et al. 2005). The survey ended with demographic information, the eating self-efficacy scale (Armitage and Connor 1999, Cronbach's alpha = .93), and suspicion probing.

Results and Discussion

Food choice. We conducted the same analysis as in Study 4. We again found a main effect of eating self-efficacy: Those high in eating self-efficacy chose healthier yogurts (1 = *healthiest option* to 9 = *unhealthiest option*), $\beta = -.66$, SE = .07, $t = -8.78$, $p < .001$. We also again observed a main effect of stimulus (human-as-machine vs. human): $\beta = 2.76$, SE = .42, $t = -6.53$, $p < .001$. There was no effect of age or gender. More important, the model again revealed the hypothesized Stimulus × Eating Self-efficacy interaction on yogurt choice, $\beta = -.48$, SE = .07, $t = -6.42$, $p < .001$.

Further spotlight analyses (M = 5.45, SD = 1.40) illustrated that the effect of the human-as-machine stimulus was again facilitative for those with high eating self-efficacy (1 SD above the mean = 6.85), who chose healthier yogurts (M = 2.28) in the human-as-machine condition than in the human condition (M = 3.33, $\beta = -.53$, SE = .14, $t = -3.68$, $p < .003$). In contrast, it again backfired among those with low eating self-efficacy (1 SD below the mean = 4.05), who chose unhealthier yogurts (M = 5.35) in the human-as-machine condition than in the human condition (M = 3.81, $\beta = .77$, SE = .14, $t = 5.41$, $p < .001$).

Expectation. The same analyses on expectation replicated the findings in Studies 3 and 4. We again found a main effect of stimulus, such that all participants in the human-as-machine condition experienced a higher expectation to choose food in a cognitive, machine-like manner, compared to those in the human condition, $\beta = .61$, SE = .19, $t = 3.19$, $p = .002$. There was no effect of eating self-efficacy, age, or gender.

From stimulus to expectation, to anticipated success, to food choice. We conducted a bias-corrected moderated serial mediation analysis to test the full proposed pathways including expectation and anticipated success/failure (Hayes 2013, customized model). This analysis revealed the following effects: First, consistent with the findings in Studies 3 and 4, we again found that viewing the human-as-machine stimulus (vs. human stimulus) heightened the expectation to adopt a cognitive, machine-like approach to food, $\beta = .47$, SE = .05, $t = 10.29$, $p < .001$, irrespective of age or gender.

Second, we found that viewing the human-as-machine stimulus decreased feelings of anticipated success, β = −.41, SE = .20, t = −2.06, *p* = .040. Third, we observed a main effect of stimulus on yogurt choice: β = 2.63, SE = .45, t = 5.82, *p < .001*; and anticipated success on yogurt choice: β = −.30, SE = .09, t = −3.26, *p = .001*, as well as an interaction of stimulus with eating self-efficacy: β = −.44, SE = .08, t = −5.57, *p < .001*. Fourth and most critically, the pathway from expectation to anticipated success was moderated by eating self-efficacy (β = .19, SE = .03, t = 7.31, *p < .001*), such that those with high eating self-efficacy anticipated success when being exposed to the activated expectation (β = .37, SE = .06, t = 6.46, *p < .001*), whereas those with low eating self-efficacy anticipated failure (β = −.17, SE = .05, t = −3.18, *p* = .002).

The full model, put together, revealed a significant serial mediation from human-as-machine stimuli to expectation, to anticipated success, to yogurt choice, while the mediational link between expectation and anticipated success was moderated by eating self-efficacy (index of moderated mediation = −.03, SE = .01, 95% CI [−.05 to −.01]): Whether consumers anticipated success in meeting the expectation of adopting a cognitive, machine-like approach to food depended on their chronic level of eating self-efficacy. The conditional indirect effects for eating self-efficacy (M = 5.45, SD = 1.40) further revealed that the expectation of adopting a cognitive, machine-like approach made consumers high in eating self-efficacy (1 SD above the mean = 6.85) anticipate success, which led to healthier choices, β = −.05, SE = .02, 95% CI [−.09 to .02]; the same expectation conversely led to anticipation of failure for those low in eating self-efficacy (1 SD below the mean = 4.05), which led to unhealthier choices, β = .02, SE = .01, 95% CI [.01 to .05].

Results without Covariates

Regression Model 1, Hayes 2013 -> DV: Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)

X - Human-as-machine vs. Human:	β = 2.73, SE = .43, t = 6.44, *p < .001*
Eating self-efficacy:	β = −.66, SE = .07, t = −8.76, *p < .001*
X x Eating self-efficacy:	β = −.47, SE = .07, t = −6.35, *p < .001*

Regression Model 1, Hayes 2013 -> DV: Expectation to Adopt a Machine-like Approach

X - Human-as-machine vs. Human:	β = .60, SE = .19, t = 3.18, *p = .002*
Eating self-efficacy:	β = .03, SE = .03, t = .93, *p* = .352
X x Eating self-efficacy:	β = .03, SE = .03, t = .77, *p* = .444

Moderated Serial Mediation, Customized Model, Hayes 2013

Outcome Variable: Expectation to Adopt a Machine-like Approach

Human-as-machine vs. Human:	β = .46, SE = .05, t = 10.26, *p < .001*

Outcome Variable: Anticipated Success

X - Human-as-machine vs. Human:	β = −.41, SE = .20, t = −2.05, *p* = .040
Expectation:	β = −.99, SE = .15, t = −6.56, *p < .001*
Eating self-efficacy:	β = −.53, SE = .14, t = −3.79, *p < .001*
X x Eating self-efficacy:	β = .09, SE = .04, t = 2.47, *p* = .014
Expectation x Eating self-efficacy:	β = .18, SE = .02, t = 7.92, *p < .001*

Outcome Variable: Healthiness of Yogurt Choice (1=healthy; 9=unhealthy)

X - Human-as-machine vs. Human:	β = 2.58, SE = .45, t = 5.71, *p < .001*
Expectation:	β = −.21, SE = .35, t = −.58, *p* = .562
Anticipated Success:	β = −.31, SE = .09, t = −3.29, *p = .001*
Eating self-efficacy:	β = −.63, SE = .32, t = −1.98, *p* = .048
X x Eating self-efficacy:	β = −.44, SE = .08, t = −5.47, *p < .001*

Expectation x Eating self-efficacy: $\beta = .02$, SE = .06, t = .37, *p = .710*

Conditional Indirect Effects
Low eating self-efficacy (4.05): $\beta = .02$, SE = .01, 95% CI [.01 to .05]
High eating self-efficacy (6.85): $\beta = -.05$, SE = .02, 95% CI [−.09 to −.02]

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