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Artificial intelligence-enabled environmental sustainability of products: Marketing benefits and their variation by consumer, location, and product types

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ABSTRACT

Firms are developing AI-enhanced products (e.g., robots) that can tackle environmental problems through autonomous interactions with their surroundings (e.g., removing waste/pollutants, tracking invasive species) and autonomous learning, which results in improved environmental performance characteristics. Such autonomous environmental benefits of products differ from conventional, static environmental benefits, which derive from pre-purchase processes and design decisions. However, the literature still lacks knowledge of how to use such autonomous environmental benefits to attract new customers. Therefore, drawing on signaling theory, this study examines the effect of these environmental benefits on a consumer's purchase intent and its variation across types of consumers, locations, and products. Based on hierarchical linear modeling of 1635 consumer evaluations of AI-enhanced products, this study finds that both static and autonomous perceived environmental benefits influence purchase intent positively. The effect of autonomous environmental benefits is stronger for women than for men and for products targeted at adults rather than children. The effect of static environmental benefits is stronger for men than women, for products targeted at children rather than adults, for consumers with a higher need for cognition, and in locations with a higher perceived environmental well-being.
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1. Introduction

An environmentally sustainable product contributes less to environmental problems than a regular product. This difference results from environmentally friendly characteristics of its materials, manufacturing processes, distribution processes, disposal/recycling processes, or product functionality (e.g., low energy consumption) (Ottman, 2011). Numerous studies report a positive effect of the perceived environmental sustainability of a product on a consumer's intent to purchase the product (Choi and Ng, 2011; Koller et al., 2011; Nyilasy et al., 2014). Owing to this effect, environmental sustainability tends to increase the profitability of a firm, despite frequently entailing higher costs (Fraj-Andrés et al., 2009). Therefore, many firms nowadays strive to enhance the environmental sustainability of their products in order to reap marketing benefits and increase their profitability (Herbas Torrico et al., 2018).

In recent years, the digital transformation of societal practices, business models, and products has aroused the interest of practitioners, scholars, and the public. Engineers have developed new digital technologies, such as artificial intelligence (AI), to enhance the environmental sustainability of products. AI refers to the intelligence displayed by advanced machines, as opposed to the natural intelligence displayed by humans and animals (Poole et al., 1998). It includes capabilities such as the autonomous understanding of the surroundings, learning from experience, decision-making, implementation of decisions, and advanced communication with humans and other machines (Russell and Norvig, 2009). AI may endow products with the ability to tackle environmental problems through autonomous actions. For example, firms are developing AI-enhanced robots that autonomously clean up houses (e.g., floor, grills, lawns, carpets, air, kitchens, microwave, garbage bins, showers, toilets, windows, roofs, pools, excrements of pets, laundry, food recycling), neighborhoods, cities, ponds, lakes, and rivers from garbage, pollutants, micro-plastics, and oil (Abrams, 2018; Chen, 2019; Community Research and Development Information Service, 2013; Gerhardt, 2020; Gowan, 2017; Gray, 2019; Knobloch, 2020; Massachusetts Institute of Technology, 2010; Peters, 2019; Sorrel, 2009; Uçar et al., 2020). Other firms are developing robots that monitor plant health and invasive

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species (e.g., snakes or fish) (CBS News, 2017; Polverino et al., 2019; Rizk and Habib, 2018), robots and AI routines that enhance the sustainability of agricultural processes and food production (Di Vaio et al., 2020; Kaab et al., 2019; Nabavi-Pelesaraei et al., 2019; Najafi et al., 2018), AI routines that automate environmental sustainability assessments of products and countries (Carlson and Sakao, 2020; Nilashi et al., 2019) and optimize energy consumption and distribution (Nižetić et al., 2019; Nosratabadi et al., 2019), and robotic vehicles that optimize routes and driving styles to minimize their carbon dioxide (CO_2) emissions (Alexander-Kearns et al., 2016; Frank, 2018; Nosratabadi et al., 2019). The magnitude of this new type of AI-enabled environmental sustainability would depend on the post-purchase, autonomous learning of an AI-enhanced product and its autonomous interactions with its local surroundings, whereas conventional environmental performance characteristics are determined by pre-purchase design and process decisions, which cannot be changed after the purchase (Ottman, 2011). Thus, this study refers to this novel, AI-enabled type of environmental sustainability as autonomous environmental benefits of a product, whereas it refers to conventional environmental sustainability as static environmental benefits of a product.

So far, no business-related research has examined the effects of AI-enabled environmental sustainability on market actors. This study aims to fill this gap in the literature and to identify ways for firms to reap marketing benefits from the development of products with AI-enabled environmental sustainability. Drawing on signaling theory (Connelly et al., 2011; Spence, 2002), it extends the literature by comparing the effects of static and autonomous environmental benefits on a consumer's intent to purchase an AI-enabled product. Moreover, it examines how the effects of static and autonomous environmental benefits vary across consumers, consumer locations, and product types. These moderators may alter the effectiveness of environmental benefits as signals of unobservable product characteristics that trigger purchase intent (Herbas Torrico et al., 2018). This study tests the hypotheses with hierarchical linear modeling of 1635 consumer evaluations of AI-enhanced products.

2. Conceptual background

2.1. The mechanisms linking environmental sustainability and purchase intent

After comparing different available products, consumers seek to purchase the product with the highest perceived value, which is the perceived gap between benefits obtained and sacrifices incurred (Zeithaml, 1988). Firms aim to maximize the perceived value of their products by increasing the level and number of benefits that a product brings to a consumer's life, by lowering the price, or by both of these strategies (Babin and Harris, 2017). However, unlike other product benefits, such as quality attributes, the environmental sustainability of a product constitutes a benefit to nature and society, rather than to an individual consumer (Ottman, 2011). Consequently, environmental sustainability had long been considered irrelevant to consumer behavior. Yet, since the 1990s, consumer research has identified positive effects of perceived environmental sustainability, which may differ from actual environmental sustainability (Sen et al., 2006), on consumer attitudes and intentions toward products (Choi and Ng, 2011; Koller et al., 2011; Martínez and Del Bosque, 2013; Nyilasy et al., 2014).

To explain such effects of perceived environmental sustainability, scholars use multiple theories. Stakeholder theory highlights the use of sustainability by a firm to build goodwill with stakeholders, such as customers, and is thus more appropriate for examining the long-term relationship between a firm and its customers (Herbas Torrico et al., 2018). By contrast, signaling theory focuses on the use of sustainability to signal desirable unobservable characteristics of a product or firm to consumers and thus also applies to first-time purchases of products (Connelly et al., 2011; Spence, 2002). This study draws on signaling theory due to its focus on novel, AI-based technology products, which most customers have not purchased yet. First, the environmental sustainability of a product signals that the firm offering the product has ethically superior values. Consumers form positive attitudes and intentions toward such products because they identify, and thus wish to associate themselves, with these values and because they seek to signal to other consumers that they also have these ethically superior values, which may improve their social relationships (Koller et al., 2011; Martínez and Del Bosque, 2013). Second, environmental sustainability signals trustworthiness (Martínez and Del Bosque, 2013). As not all quality characteristics of a product can be observed before the purchase (e.g., long-term reliability, detailed functionality), consumers draw upon this signal of trustworthiness to make inferences regarding unobservable quality characteristics, which translates into favorable attitudes and intentions toward the product (Herbas Torrico et al., 2018; Martínez and Del Bosque, 2013). Consequently, this present study adopts signaling theory (Connelly et al., 2011; Spence, 2002) to develop its hypotheses.

2.2. Artificial intelligence and environmental sustainability

In the field of engineering, several studies address the potential for artificial intelligence (AI) to enhance the environmental sustainability of products. Likewise, numerous firms are developing products, where AI enhances the degree of environmental sustainability. However, in the field of business, no research appears to examine the effects of AI-based enhancements of environmental sustainability on market players' attitudes and behaviors. To extend the literature, this study explores the effects of the AI-enhanced environmental sustainability of a product on a consumer's purchase intent.

To contrast AI-enhanced and conventional types of environmental sustainability and thus highlight the differences between these two concepts, this study divides the different environmental benefits of a product, which together comprise its overall environmental sustainability, into two groups. First, it defines *static* environmental benefits as the environmental benefits that result from pre-purchase design, production, and distribution processes of a product, which cannot be changed or undone after the purchase. For instance, the CO_2 emissions during the manufacturing of a product, the choice of product materials, and the development of energy-saving functionalities of a product cannot be undone after selling the product to consumers. While a part of the post-purchase environmental impact of a product depends on the extent of its post-purchase use, the eco-friendly nature of technological features (e.g., whether a car is energy-efficient or not) is determined in pre-purchase development processes. Static environmental benefits correspond to the traditional notion of environmental sustainability, whose effect on consumer behavior is already known (Choi and Ng, 2011; Koller et al., 2011; Martínez and Del Bosque, 2013; Nyilasy et al., 2014). Second, this study defines *autonomous* environmental benefits as the ability of an AI-enhanced product to autonomously identify environmental problems, learn and find solutions, and carry out self-determined actions to tackle these environmental problems. While the extent of static environmental benefits is determined by the pre-purchase design, production, and distribution of products, autonomous environmental benefits arise from post-purchase autonomous interactions between an AI-enhanced product and its environment, which include learning and decision-making. For instance, a household robot might autonomously clean up the house and its surroundings from dust, mold, garbage, and pollutants with tools and devices it purchases and picks up autonomously. Alternatively, it might analyze the consumer's eating habits, identify environmentally friendlier (e.g., organic) options, procure these items, and optimize the cooking procedures to minimize their environmental footprint.

The literature on environmental marketing and business has not yet addressed autonomous environmental benefits. Drawing on signaling theory (Connelly et al., 2011; Spence, 2002), this study extends the literature by exploring the effect of autonomous environmental benefits on consumer behavior and by comparing it with the effect of static environmental benefits. Moreover, it examines how these effects vary by the consumer's gender, need for cognition, location, and evaluated product type. According to signaling theory (Connelly et al., 2011; Spence, 2002), the influence of a signal (e.g., the environmental sustainability of a product) depends on the receiver's interpretation of the signal (i.e., the consumer) and on the value of the signal in the receiver's situation (i.e., location, product context). Fig. 1 provides an overview of the conceptual framework of this study.

3. Development of hypotheses

3.1. AI and non-AI types of environmental sustainability: effects on product purchase intent

Drawing on signaling theory (Connelly et al., 2011; Spence, 2002), scholars argue that the perceived environmental sustainability of a product affects purchase intent positively because it serves as a signal of the trustworthiness and values of the firm offering the product (Herbas Torrico et al., 2018). This signal enhances the consumer's quality perception (Koller et al., 2011; Martínez and Del Bosque, 2013), identification with the brand (Martínez and Del Bosque, 2013), and desire to use the product as a means of signaling own values to the social environment (Koller et al., 2011). In turn, these mechanisms enhance the consumer's intent to purchase the product (Choi and Ng, 2011; Herbas Torrico et al., 2018; Koller et al., 2011; Martínez and Del Bosque, 2013; Nyilasy et al., 2014). While this argumentation concerns perceived environmental sustainability in the traditional sense, which this study refers to as perceived static environmental benefits, it may equally apply to the perceived autonomous environmental benefits of an AI-enhanced product. Once consumers perceive such benefits before the purchase, they likely add them to the sum of environmental benefits expected, which would amplify the signal of environmental sustainability and the consumer's resultant response. Autonomous environmental benefits may be even more influential than static ones because the consumer has a certain authority over the autonomous (not predetermined and static) behavior of an AI-enhanced product, whose actions can thus serve as a stronger social signal of the consumer's own values. For example, when a consumer directs an AI-enhanced humanoid household robot to clean up garbage and pollutants in the neighborhood, the social environment is likely to interpret these actions as a signal of the consumer's own values.

H1a. Perceived static (non-AI) environmental benefits have a positive effect on product purchase intent.

H1b. Perceived autonomous (AI-enabled) environmental benefits have a positive effect on product purchase intent.

3.2. The effects of environmental sustainability types: differences by consumer

According to signaling theory (Connelly et al., 2011; Spence, 2002), the influence of a signal, such as the environmental sustainability of a product, depends on the receiver's interpretation of the signal. Since different consumers may differ in their interpretation of the signal of environmental sustainability, the effects of static and autonomous environmental benefits on purchase intent may vary across consumers. Specifically, they may differ between male and female consumers, whose different social roles affect their susceptibility to signals of different unobserved characteristics of a firm or product (Frank et al., 2014). They may also vary by the consumer's preference for effortful thinking as signals differ in their degree of abstraction and may thus require different degrees of effortful thinking to decode these signals.

Differences by gender. According to the literature, women are more risk-averse than men and thus more sensitive to signals of trustworthiness (Schwartz and Rubel, 2005), also in their purchasing decisions (Frank et al., 2014). Moreover, gender roles cause women to show a greater desire to signal to their social environment that they adhere to social rules, whereas men have more freedom, or are even socially expected, to sometimes deviate from social rules to show their audacity and braveness (Holmes, 2013). Consequently, the literature reports greater effects of environmental sustainability on consumer behavior for women than men (Lee, 2009; Sudbury Riley et al., 2012; Wang et al., 2018), although Mostafa (2007) reports the opposite tendency. This literature focuses only on perceived static (non-AI) environmental benefits. However, the argumentation can be extended to perceived autonomous environmental benefits, which constitute a contribution to society through the actions of an AI-enhanced product and thus

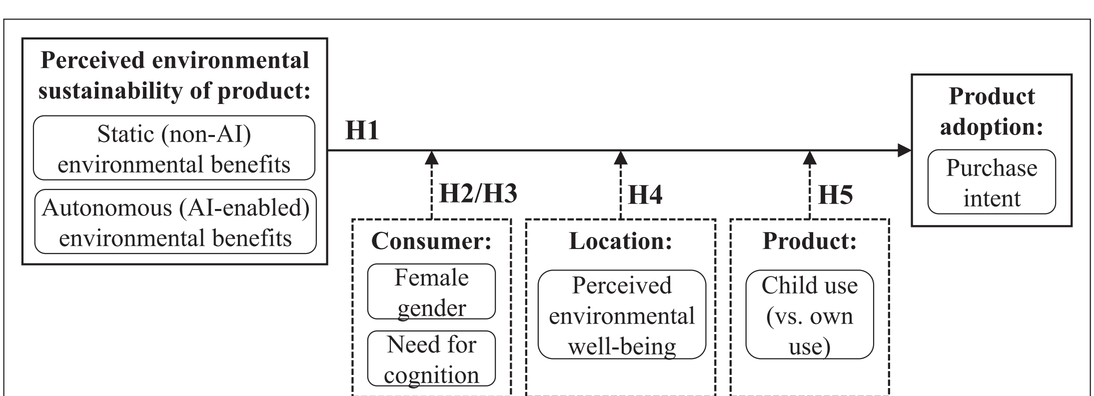

Fig. 1. Conceptual framework and hypotheses.

also are a signal of trustworthiness and socially desirable values. In particular, the gender difference in the consumer's importance attached to signaling one's own values may be even stronger for autonomous environmental benefits than for static ones because the consumer's authority over the (non-static) actions of an AI-enhanced product makes it more likely that the social environment attributes these actions to the consumer's own values. The expectation of such social recognition would increase the consumer's motivation to purchase the product in order to signal one's own values to others (Koller et al., 2011).

H2a. The effect of perceived static environmental benefits on product purchase intent is stronger for women than for men.

H2b. The effect of perceived autonomous environmental benefits on product purchase intent is stronger for women than for men.

Differences by need for cognition. While perceived environmental sustainability serves as a signal of values and trustworthiness (Herbas Torrico et al., 2018; Koller et al., 2011; Martínez and Del Bosque, 2013), the concept (e.g., the relationship between product attributes and global warming) is abstract and difficult to understand (Ottman, 2011; Vainio, 2019). Moreover, the environmental footprint of production processes and product materials is difficult to observe, and a solid understanding thus requires knowledge and contemplation (Ottman, 2011; Sen et al., 2006). Therefore, deeper thinking may lead consumers to a better understanding of the relevance of static environmental benefits, which is necessary for interpreting them as a signal of trustworthiness and values. In psychology, a consumer's tendency for deep thinking is captured by the need for cognition, which reflects the preference for deep, rather than simple and less effortful, thinking (Cacioppo et al., 1984). Thus, this study posits that a higher need for cognition enhances the interpretation of static environmental benefits as a signal of trustworthiness and values, and consequently strengthens the effect of perceived static environmental benefits on purchase intent. Among the limited research about such a mechanism, one study supports such a mechanism in analyzing the effects of social (not environmental) advertising (Yang, 2018), whereas another one fails to support it in analyzing reasons for environmentally friendly food choices (Vainio, 2019).

Contrary to the previous moderating effect, this study posits that a consumer's need for cognition weakens the effect of autonomous environmental benefits on purchase intent for two reasons. First, autonomous environmental benefits originate not in the pre-purchase phase, but in the use phase of an AI-enhanced product, and are thus easy to observe and comprehend. Second, the primary appeal of the autonomous environmental benefits of an AI-enhanced product is that these actions are autonomous and liberate the consumer from effortful thoughts and decisions. Thus, autonomous environmental benefits may appeal more to consumers with a low need for cognition, who wish to minimize effortful thinking.

H3a. The effect of perceived static environmental benefits on product purchase intent is stronger for consumers with a higher need for cognition.

H3b. The effect of perceived autonomous environmental benefits on product purchase intent is weaker for consumers with a higher need for cognition.

3.3. The effects of environmental sustainability types: differences by situational context

According to signaling theory (Connelly et al., 2011; Spence, 2002), the influence of a signal, such as the environmental sustainability of a product, depends on its value in the receiver's situational context (i.e., location, product context). When consumers interpret the environmental sustainability of a product as a signal that is more valuable to their situation, they are more likely to purchase the product.

Consumer location. Regarding the consumer's location, the literature reports differences in the effect of static environmental benefits on consumer behavior between urban and rural locations (Tanner et al., 2004) and between countries (Liobikienė et al., 2016). As an extension, this study explores how the effects of environmental benefits vary by the perceived environmental well-being (i.e., the perceived state of the local environment) at the consumer's location.

In a location with a lower perceived environmental well-being, a consumer may interpret the environmental benefits of a product as a more important signal because they offer a path for improving the environmental well-being by purchasing the product. A lower perceived environmental well-being in the consumer's location may thus strengthen the effect of environmental benefits on purchase intent. Contrary to this value mechanism, a more polluted environment may cause the consumer to get used to, and become less sensitive to, environmental problems and their solutions (Hu and Frank, 2019). This sensitivity mechanism would suggest that a lower environmental well-being reduces the consumer's sensitivity to the signal of environmental benefits and thus weakens their effect on purchase intent.

To resolve the balance between these two opposing effects, this study highlights the location where the environmental benefits of a product materialize. Autonomous environmental benefits materialize in the consumer's location, where the AI-enhanced product engages in autonomous actions that alleviate environmental problems. These benefits are more valuable when the consumer's location suffers from more environmental problems that the AI-enhance product can address. Consequently, this study posits that the perceived autonomous environmental benefits of a product are a more valuable signal in a location with a lower perceived environmental well-being, where they exert a stronger effect on the consumer's intent to purchase the product. By contrast, static environmental benefits originate in the pre-purchase design, production, and distribution phases of a product (Ottman, 2011), which mostly take place in a location different from the consumer's local community. These benefits are thus less valuable for improving a low perceived environmental well-being in the consumer's own location. Consequently, in a location with a lower environmental well-being, the mechanism of lower sensitivity to static environmental benefits may outweigh the mechanism of a higher value of static environmental benefits for improving the environment. Thus, this study posits that perceived static environmental benefits have a weaker effect on purchase intent in a location with a lower perceived environmental well-being.

H4a. The effect of perceived static environmental benefits on product purchase intent is stronger in a consumer location with a higher environmental well-being.

H4b. The effect of perceived autonomous environmental benefits on product purchase intent is weaker in a consumer location with a higher environmental well-being.

Product type. While the environmental benefits of a product serve as a signal of trustworthiness (Martínez and Del Bosque, 2013), the importance of this signal depends on how protective the consumer is of the intended user of the product. Since humans instinctively seek to protect children (Winston, 2011), adult consumers likely attribute a greater importance to signals of trustworthiness when purchasing products for children. Thus, this study posits that the effect of static environmental benefits, as a signal of trustworthiness, on purchase intent is stronger when adult consumers purchase products targeted at children (e.g., toys), than when they purchase products targeted at themselves or other adults (e.g., cars). While this mechanism would also extend to autonomous environmental benefits, consumers may interpret the autonomous actions of an AI-enhanced product, which is a machine lacking human empathy and childcare instincts, as a threat to children (Wong, 2016). This may weaken the interpretation of autonomous environmental benefits as a signal of trustworthiness in adult consumers purchasing AI-enhanced products for children. Hence, this study posits that the effect of autonomous environmental benefits on purchase intent is weaker when adult consumers purchase products targeted at children (e.g., toys) than when they purchase products targeted at themselves or other adults (e.g., cars).

H5a. The effect of perceived static environmental benefits on purchase intent is stronger for products designed for use by children than for products designed for an adult consumer's own use.

H5b. The effect of perceived autonomous environmental benefits on purchase intent is weaker for products designed for use by children than for products designed for an adult consumer's own use.

4. Method

4.1. Measurement tool

To measure the variables and prepare for testing the hypotheses about the causes of variation in purchase intent, a questionnaire was developed for a survey of consumer attitudes toward AI-enabled products that are sold on consumer markets and can move when carrying out AI-based decisions. As types of AI-enabled products, this study uses autonomous vehicles, robotic pets (for child use as required for testing H5), robotic vacuum cleaners, and humanoid household robots. This diversity ensures the ability to generalize the results beyond specific product contexts. Moreover, obtaining responses on multiple products from the same, rather than separate, respondents prevents misinterpreting observed attitudinal differences across products that actually result from unobserved sample differences (Frank et al., 2014). Moreover, this specific choice of products focuses on AI-enabled products that are widely expected to play a role in the future and thus have a high likelihood of predicting effects representative of the future. The appendix lists the construct scales and their literature sources. It also includes the scales of two control variables: product-related expertise and product-related environmental expertise.

4.2. Data collection and sample

The data collection targeted China, where environmental sustainability plays an important role in order to tackle the severe environmental problems of the country (Xu and Lin, 2016). Moreover, since Chinese firms are at the forefront of AI development (Allen, 2019), AI-enabled products are more widely available than in other countries that suffer from similar environmental problems. In addition, China exhibits large regional differences in its environmental problems (Xu and Lin, 2016), which provides fertile ground for testing the role of perceived environmental well-being in the consumer's location (H4). Consequently, the choice of China may allow for a more reliable testing of the hypotheses than would the choice of an alternative country with fewer and less geographically diverse environmental problems and with a lower understanding of AI-enhanced products in the population.

Data were collected across mainland China at firms, public institutions, public places, universities, and shopping malls via both an offline survey and an online survey, which led to 44% of the responses. Respondents received an incentive valued RMB 30 from a famous e-commerce platform. After removing missing data, the final sample includes 438 respondents, who provided 1635 evaluations of the four AI-enhanced products. For the purpose of testing the effects of consumer location (H4), the sample covers all regions of mainland China except for Tibet, whose environment and population have particular features. The sample is distributed evenly across men and women. It is slightly younger than the population, which matches the greater likelihood of young consumer to purchase modern technology products (Frank et al., 2015). Table 1 presents the correlations and descriptive statistics of the variables. These statistics reveal that the sample consists of consumers with average expertise and purchase intentions, who may be considered representative of regular consumers found in the marketplace.

4.3. Data validity

Non-response bias. A comparison of early and late respondents does not indicate any differences, making non-response bias unlikely (Armstrong and Overton, 1977).

Common method variance (CMV). CMV may bias the conclusions of statistical analysis. Lindell and Whitney (2001) provide an established guideline for estimating the extent of CMV that is considered stricter and more accurate than traditional approaches such as Harman's single factor test, which this study and most others pass. They argue that the smallest correlation between variables in a dataset can serve as an upper bound on CMV. This smallest correlation is .07 in this study and .08 for the dependent variable of purchase intent (see Table 1), which implies only a limited extent of possible CMV. Moreover, as another established approach to estimating the extent of CMV, this study includes the marker variable of loneliness, which is theoretically unrelated to the key variables in the study, as required by Lindell and Whitney (2001). It is measured on a 3-item, 7-point Likert scale (Hughes et al., 2004), which entails higher measurement reliability and accuracy than a scale with fewer items and response points, and fulfills the standard criteria of convergent and discriminant validity: "I often feel that I lack companionship"/"I often feel left out"/"I often feel isolated from others" (Cronbach's $\alpha = .83$, average variance extracted (AVE) $= .65 >$ all squared correlations). The seven correlations between this marker variable and the other reflective variables of the model range from $-.01$ and .05. Five of them are between $-.01$ and .01, three are negative, four are positive, and six are non-significant. These small correlations and their distribution around zero imply that this study does not appear to suffer from CMV.

Convergent and discriminant validity. Table 1 shows that all multi-item constructs fulfill the criteria of convergent and discriminant validity (Hair et al., 2010): Cronbach's $\alpha > .7$, composite reliability > .7, AVE > .5, and AVE > squared correlations with other constructs. The second-order construct of static (non-AI) environmental benefits is based on first-order constructs related to the pre-use ($\alpha = .95$; AVE = .79), use ($\alpha = .98$; AVE = .89), and post-use ($\alpha = .95$; AVE = .83) phases of the product life cycle (see appendix). These first-order constructs also fulfill the criteria of convergent and discriminant validity. In addition, the fit measures of a confirmatory factor analysis fulfill the standard acceptance criteria of χ^2/df < 5, CFI $\geq .95$, RMSEA $\leq .07$, and upper bound of 90% RMSEA confidence interval $\leq .1$ (Hair et al., 2010): χ^2/df = 2.94, CFI = .99, RMSEA = .03, upper bound of 90% RMSEA confidence interval = .04.

Table 1
Correlations and descriptive statistics of constructs.

Variables	Correlations								
	1	2	3	4	5	6	7	8	9
Consumer									
1 Female gender (1: female; 0: male)									
2 Need for cognition	-.21								
Consumer location									
3 Perceived environmental well-being	-.06	.08							
Product									
4 Product-related expertise	-.16	.14	.11						
5 Product-related environmental expertise	-.12	.15	.17	.50					
6 Child use (1: for child use; 0: for own use)	.00	-.01	-.01	-.14	-.12				
Environmental sustainability									
7 Static (non-AI) environmental benefits (2nd-order construct)	-.06	.09	.08	.22	.38	-.13			
8 Autonomous (AI-enabled) environmental benefits	-.07	.12	.07	.17	.35	-.18	.55		
Product adoption									
9 Purchase intent	-.14	.18	.08	.33	.40	-.20	.37	.38	
Descriptive statistics									
Mean	.55	4.40	4.36	2.74	3.12	.24	3.90	3.93	3.48
Standard deviation	.50	1.31	1.46	1.53	1.54	.43	1.29	1.57	1.87
Average variance extracted	n/a	.67	.85	.93	.92	n/a	.63	.82	.92
Cronbach's α	n/a	.82	.92	.96	.96	n/a	.84	.95	.97

Notes: All correlations $|r| \geq .05$ are significant at $p < .05$ (two-sided). Descriptive statistics for mean score across non-standardized items.

5. Results

5.1. Hypothesis tests

Model structure. Table 2 presents the results of the hypothesis tests. To account for the nested data structure of consumer evaluations of up to four product types, the hypotheses are tested using hierarchical linear modeling (HLM) with product evaluations at level 1 and consumers at level 2, whereas the alternative use of regression analysis would not properly account for the nested structure of the data. Product purchase intent serves at the dependent variable. As control variables, the HLM model includes the consumer's gender (1: female; 0: male), need for cognition, perceived environmental well-being in the consumer's local community, self-assessment of product-related expertise, and self-assessment of product-related environmental expertise. Moreover, it controls for whether the product type is primarily targeted at children (1: for child use; 0: for own use), which is the case for robotic pets, but not for the other product types. It also includes an intercept and level-specific error terms. To test the hypotheses, the HLM model further includes the consumer's perception of static (non-AI) environment benefits (H1a) and autonomous (AI-enabled) benefits of the product (H1b). In addition, it includes two-way interaction terms calculated by multiplying these consumer perceptions by gender (H2), need for cognition (H3), perceived environmental well-being (H4), and product type (H5) after standardizing all variables. The model also includes an intercept and level-specific error terms. According to the pseudo R^2 values, the model explains 23% of the variance in purchase intent across product types for the same consumer and 43% of the variance in purchase intent across different consumers. As in similar studies, these values reflect that consumers' purchasing decisions are based not only on environmental sustainability, but also on other factors such as product and service quality, price, and brand reputation (Frank et al., 2014, 2015).

Main effects. The results indicate that purchase intent is higher for women than men and for consumers with a high need for cognition and a high product-related overall expertise and environmental expertise. It is higher for product types targeted at adult consumers, rather than at children (i.e., robotic pets). Both static (non-AI) and autonomous (AI-enabled) perceived environmental benefits have positive effects on purchase intent, which supports the hypotheses H1a and H1b. The effect of autonomous environmental benefits is slightly larger, in nominal terms, than the effect of static environmental benefits.

Moderating effects. The effect of static environmental benefits on purchase intent is larger for men than for women (H2a not supported), for consumers with a higher need for cognition (H3a supported), for consumers who perceive the environmental well-being in their local community as better (H4a supported), and for products targeted at children, rather than at adult consumers (H5a supported). By comparison, the effect of autonomous environmental benefits on purchase intent is larger for women than for men (H2b supported), and for products targeted at adult consumers, rather than at children (H5b supported). The strength of this effect does not vary by the need for cognition (H3b not supported) and the perceived environmental well-being (H4b not supported). Fig. 2 visualizes the moderating effects. In line with the use of standardized variables in the analysis of Table 2, Fig. 2 uses standard deviations from the mean as axis units and designates ± 1 standard deviation as high/low values of continuous moderating variables. The alternative use of a stronger departure from the mean for high/low values of moderators causes a proportionally stronger variation in the slopes depicted in Fig. 2.

5.2. Robustness tests and additional analyses

Quadratic terms. When adding quadratic terms of all continuous

Table 2
Effects of perceived environmental benefits on product purchase intent.

Independent variables	β
Intercept	-.015
Consumer:	
Female gender (1: female; 0: male)	-.061*
Need for cognition	.096***
Consumer location:	
Perceived environmental well-being	-.002
Product:	
Product-related expertise	.135***
Product-related environmental expertise	.162***
Child use (1: for child use; 0: for own use)	-.111***
Perceived environmental sustainability of product:	
Static (non-AI) environmental benefits (H1a: +)	.152***
Autonomous (AI-enabled) environmental benefits (H1b: +)	.183***
The effects of environmental sustainability: differences by consumer	
Female gender × Static environmental benefits (H2a: +)	-.089***
Female gender × Autonomous environmental benefits (H2b: +)	.063**
Need for cognition × Static environmental benefits (H3a: +)	.059*
Need for cognition × Autonomous environmental benefits (H3b: −)	-.018
The effects of environmental sustainability: differences by consumer location	
Perceived environmental well-being × Static environmental benefits (H4a: +)	.068**
Perceived environmental well-being × Autonomous environmental benefits (H4b: −)	-.009
The effects of environmental sustainability: differences by product	
Child use × Static environmental benefits (H5a: +)	.044*
Child use × Autonomous environmental benefits (H5b: −)	-.050*
Fit statistics:	
HLM pseudo R^2 (level 1: product evaluation)	.225
HLM pseudo R^2 (level 2: consumer)	.428
Sample size	1635

Notes: *p < .05; **p < .01; ***p < .001 (two-sided p-values). Hierarchical linear modeling (HLM). Effects of standardized variables and their interactions.

variables to the analysis, none of these quadratic terms is significant, and all hypothesis tests lead to identical conclusions.

Static environmental benefits: one first-order construct. When operationalizing static environmental benefits not as a second-order construct based on first-order sub-dimensions, but as merely one first-order construct ($\alpha = .96$; AVE = .65), then all conclusions related to the hypothesis tests remain identical. At the same time, the confirmatory factor analysis indicates much better fit for a second-order construct.

All constructs formative. When operationalizing all multi-item measures not as reflective constructs (i.e., factors), but as formative constructs (i.e., indices) calculated as an average of their measurement items, then all hypothesis tests lead to identical conclusions.

Sub-dimensions of static environmental benefits. An additional analysis replaced the second-order construct of static environmental benefits by its sub-dimensions of static environmental benefits in the pre-use, use, and post-use phases of the product life cycle. The results indicate that the observed gender difference in the effect of static environmental benefits (H2a) relates to environmental benefits in the use (e.g., low energy consumption and CO_2 emissions while using the product) and post-use (e.g., recycling) phases of the product life cycle. Moreover, the moderating effects of need for cognition (H3a) and perceived environmental well-being (H4a) on the effect of static environmental benefits both relate to the pre-use phase (i.e., manufacturing and distribution). Finally, the observed product differences in the effect of static environmental benefits (H5a) relate to environmental benefits in the use phase.

6. Discussion

6.1. Short summary

This study explores the ability of AI to increase both the perceived environmental sustainability of a product and, consequently, a consumer's intention to purchase this product. To this end, this study compares the effects of autonomous (AI-enabled) and static (conventional) perceived environmental benefits of a product on purchase intent and examines the variation of these effects by type of consumer, location, and product. It finds that both static and autonomous perceived environmental benefits affect purchase intent positively (H1a/H1b supported). The effect of perceived autonomous environmental benefits is stronger for women than for men (H2b supported) and for products targeted at adults rather than at children (H5b supported). However, it does not vary by the consumer's need for cognition and by the perceived well-being of the environment in the consumer's location (H3b, H4b not supported). The effect of static environmental benefits is stronger for men than for women (contrary to H2a), for products targeted at children rather than at adults (H5a supported), for consumers with a higher need for cognition (H3a supported), and in locations with a higher perceived environmental well-being (H4a supported).

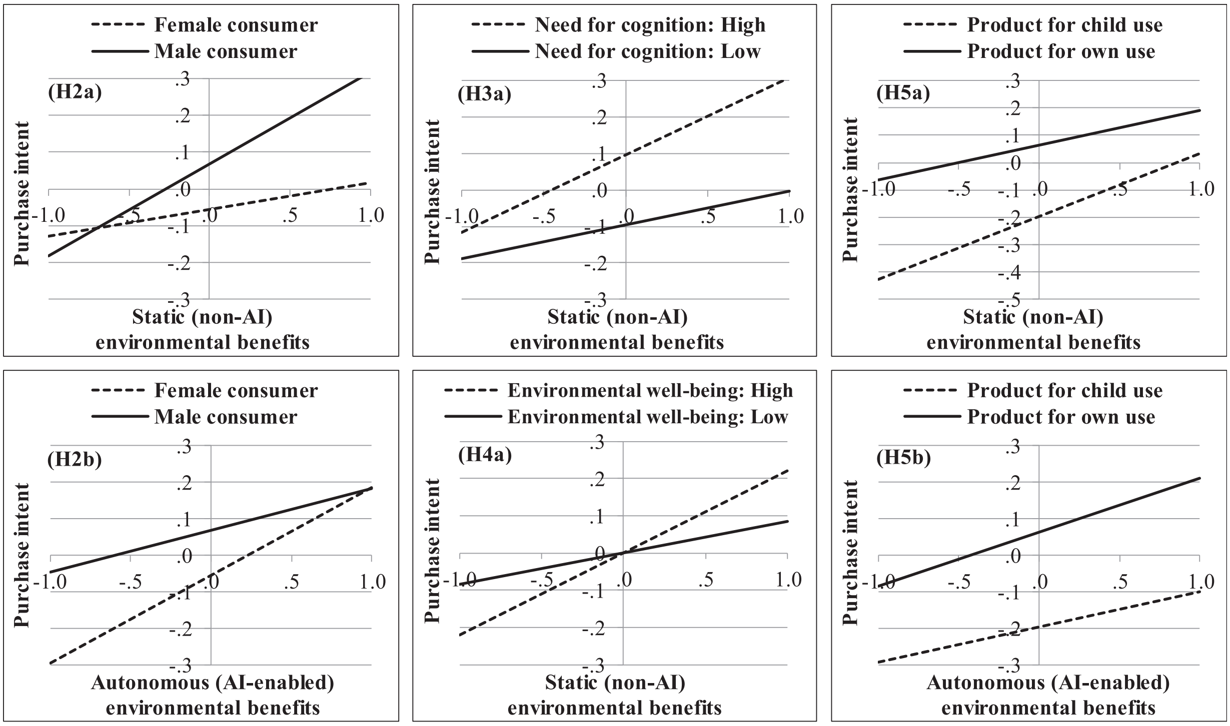

Fig. 2. Visualization of moderating effects. Notes: Axis unit: standard deviations from mean. Moderator unit for high/low in the case of continuous variables: ±1 standard deviation from mean.

6.2. Theoretical implications

This study makes several contributions to theory. First, it extends signaling theory (Connelly et al., 2011), as a theoretical lens for explaining the effects of conventional environmental sustainability (Herbas Torrico et al., 2018), into the new age of AI-enabled environmental sustainability. It demonstrates that the integration of AI into products can boost the level of perceived environmental sustainability and, thus, its effectiveness as a signal that triggers purchase intentions. Hence, AI can benefit nature and marketers alike. AI-enabled, autonomous environmental benefits appear to have an even stronger effect on purchase intent than do conventional, static environmental benefits. The marketing benefits of static environmental benefits are limited by their abstract nature and by the difficulty for consumers to observe them during design, manufacturing, and distribution processes in the pre-purchase phase of a product (Ottman, 2011). These characteristics attenuate the effectiveness of static environmental benefits as a signal of trustworthiness and values. Hence, static environmental benefits have a strong effect only on consumers with a high need for cognition, whose deeper thinking helps them to comprehend the abstract and unobservable environmental characteristics of a product. By contrast, autonomous environmental benefits in the form of autonomous actions that an AI-enhanced product (e.g., robot) carries out in front of the consumer's eyes are easy to observe and thus effective as a signal, which boosts their influence on consumer intentions. This also ensures that a broader set of consumers, including those with a low need for cognition, can understand these benefits and respond to them by forming purchase intentions.

Second, several studies find a greater effect of perceived static environmental benefits on female consumers than on male consumers (Lee, 2009; Sudbury Riley et al., 2012; Wang et al., 2018). The present study confirms such a tendency only for perceived autonomous environmental benefits. By contrast, it finds the opposite tendency of a greater effect of static environmental benefits for men than for women, which corresponds to the results obtained by Mostafa (2007). This might be caused by men's greater interest in, and knowledge of, technology products (Frank et al., 2015), which may translate into a deeper comprehension of the abstract, unobservable static environmental benefits of a product and thus into a stronger signaling mechanism, whose strength depends on the extent of knowledge held (Sen et al., 2006).

Third, this study is the first to explore how perceived environmental well-being in the consumer's location moderates the signaling effect of perceived environmental sustainability that triggers purchase intentions. Similar to recent findings by Hu and Frank (2019) for non-AI settings, it finds a positive moderating effect on the effect of perceived static environmental benefits. However, it does not find such a moderating effect on the effect of perceived autonomous environmental benefits. Environmental pollution may decrease a consumer's sensitivity to abstract, unobservable environmental benefits as a signal of values and trustworthiness, whereas it does not appear to decrease the consumer's sensitivity to environmental actions that take place in front of the consumer's eyes (i.e., autonomous environmental benefits). In studying similar moderating effects of the perceived well-being of the global, not local, environment, Dagher and Itani (2014) find a negative moderating effect of perceived static environmental benefits, whereas Lee (2009) reports a positive moderating effect, but only for female adolescents. In light of such limited evidence, the present study lends credence to a positive effect, irrespective of gender.

Fourth, this study is the first to compare the effects of perceived environmental benefits of products targeted at adult consumers with those of products targeted at children, for whom adults purchase such products. Since adults tend to be protective of children, they value signals of trustworthiness more in caring for their children (Winston, 2011). Consequently, this study finds that perceived static environmental benefits are more influential for products targeted at children. By contrast, perceived autonomous environmental benefits are less influential for products targeted at children than for those targeted at adults. This is likely because consumers consider the autonomous actions of an AI-enhanced product lacking human empathy as a safety risk (Tussyadiah and Park, 2018; Wong, 2016) and may thus be more hesitant when purchasing such a product for children, of whom they are protective (Winston, 2011), also because children have a low ability to protect themselves as consumers (Frank, 2012).

6.3. Implications for managers and public policy makers

While managers tend to think of AI functions in products as beneficial for saving a consumer's time by automating manual processes (Wong, 2016), this study shows that AI can also lead to very different, environmental benefits, which appear to trigger strong purchase intentions in consumers. These AI-enabled, autonomous environmental benefits are more influential than conventional, static environmental benefits. Moreover, they do not suffer from the limited response to static environmental benefits by consumers with a preference for simpler thoughts (Yang, 2018) and by consumers residing in polluted areas. Hence, marketers can use them for targeting a broader set of consumers. In addition, the combination of both static and autonomous environmental benefits can help appeal to both female consumers, who are more sensitive to autonomous environmental benefits, and male consumers, who are more sensitive to static environmental benefits. However, while static environmental benefits tend to be effective in products for children (e.g., organic baby food), autonomous environmental benefits may scare parents away and may thus be less effective when targeting parents purchasing products for children.

Public policy makers and social activists frequently discuss the perils of AI in controlling people, eliminating people's jobs, and engaging in emotionless actions that hurt people (Crist, 2019; Kak, 2018). Contrary to such negative stereotypes, this study shows that AI may boost the environmental sustainability of products in a way that increases consumers' purchase intentions and, consequently, also firms' prospective sales. This would contribute to public policy goals by increasing firms' motivations to protect the environment and by leading to new employment opportunities at firms offering AI-enhanced products (Reese, 2019). Moreover, the spread of AI-enhanced products with autonomous environmental benefits would help increase the manpower required to address environmental problems.

6.4. Limitations and directions for future research

A limitation of this study is its focus on a topic of the future, which has lower certainty than a description of present consumer behavior and can only measure intentions, as opposed to actual behavior in the future. Consumers' perceptions and preferences may evolve over time as AI becomes more powerful, reliable, and normal to consumers. Moreover, this study examines only four product types. However, it intends to spark a discussion and encourage follow-up research about hitherto overlooked opportunities that may arise from AI to improve both the environment and other valuable aspects of a consumer's life. Such opportunities can increase the product sales of firms. Aside from this main topic, this study touches upon two hitherto unaddressed research questions worthy of future scholarly inquiry. First, the literature does not address the relationship between environmental problems in the consumer's location and the consumer's demand for environmentally friendly products as a possible solution to these environmental problems. Despite the seemingly apparent connection between environmental problems and solutions, this relationship may be complicated as detailed in the development of H4 and found in the counterintuitive results of this study. Future research could disentangle the sensitivity and value mechanisms underlying this relationship in non-AI settings. Second, scholars may examine more broadly in non-AI settings how the consumer's attention to environmental sustainability differs between purchases of gifts for others and purchases for consumers themselves.

6.5. Conclusion

The integration of AI into products represents an opportunity to boost the environmental sustainability of these products and, thereby, to increase consumers' purchasing intentions and appeal to new consumer segments less attracted by conventional environmental sustainability. Hence, AI-enabled environmental sustainability can help firms to build new competitive advantage and more effectively market their offerings to consumers. At the same time, this effectiveness varies by the type of consumers and products. Compared with conventional environmental sustainability, AI-based environmental sustainability offers a path to appeal more to female consumers, which may enable firms to use environmental sustainability to more broadly engage consumers across social boundaries and secure additional sales while benefitting the environment. At the same time, consumers do not appear to welcome AI-based environmental sustainability when buying products for children, which constitutes a boundary condition in its use for marketing purposes.

CRediT authorship contribution statement

Björn Frank: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.125242.

References

Abrams, M., 2018, May 16. Remote Robot Cleans Trash from Water. American Society for Mechanical Engineers, New York. https://www.asme.org/topics-resources/content/remote-robot-cleans-trash-water.

Alexander-Kearns, M., Peterson, M., Cassady, A., 2016, November 18. The Impact of Vehicle Emissions on Carbon Emissions. Center for American Progress, Washington, DC. https://www.americanprogress.org/issues/green/reports/2016/11/18/292588/the-impact-of-vehicle-automation-on-carbon-emissions-where-uncertainty-lies.

Allen, G.C., 2019, February 6. Understanding China's AI Strategy: Clues to Chinese

Strategic Thinking on Artificial Intelligence and National Security. Center for a New American Security, Washington, DC. https://www.cnas.org/publications/reports/understanding-chinas-ai-strategy.
Armstrong, J.S., Overton, T.S., 1977. Estimating nonresponse bias in mail surveys. J. Market. Res. 14 (3), 396–402.
Babin, B.J., Harris, E., 2017. Consumer Behavior, eighth ed. Cengage, Boston, MA.
Cacioppo, J.T., Petty, R.E., Feng Kao, C., 1984. The efficient assessment of need for cognition. J. Pers. Assess. 48 (3), 306–307.
Carlson, A., Sakao, T., 2020. Environmental assessment of consequences from predictive maintenance with artificial intelligence techniques: importance of the system boundary. Procedia CIRP 90, 171–175.
CBS News, 2017. "Weird and Wired" Tech helps Battle Invasive Species. New York. https://www.cbsnews.com/news/robots-tasers-technology-join-battle-against-invasive-species/.
Chen, C., 2019, May 15. 12 Smart Home Gadgets that Practically Clean the House for You. Insider, New York. https://www.businessinsider.com/best-cleaning-gadgets-2018-1.
Choi, S., Ng, A., 2011. Environmental and economic dimensions of sustainability and price effects on consumer responses. J. Bus. Ethics 104 (2), 269–282.
Community Research and Development Information Service, 2013, May 1. Robots Designed to Clean up Our Streets. Science X. Douglas, Isle of Man: Omicron. https://phys.org/news/2013-05-robots-streets.html.
Connelly, B.L., Certo, S.T., Ireland, R.D., Reutzel, C.R., 2011. Signaling theory: a review and assessment. J. Manag. 37 (1), 39–67.
Crist, R., 2019, July 13. Amazon and Google Are Listening to Your Voice Recordings: Here's What We Know about That. CNET. https://www.cnet.com/how-to/amazon-and-google-are-listening-to-your-voice-recordings-heres-what-we-know.
Dagher, G.K., Itani, O., 2014. Factors influencing green purchasing behaviour: empirical evidence from the Lebanese consumers. J. Consum. Behav. 13 (3), 188–195.
Di Vaio, A., Boccia, F., Landriani, L., Palladino, R., 2020. Artificial intelligence in the agri-food system: rethinking sustainable business models in the COVID-19 scenario. Sustainability 12 (12), 4851.
Fraj-Andrés, E., Martinez-Salinas, E., Matute-Vallejo, J., 2009. A multidimensional approach to the influence of environmental marketing and orientation on the firm's organizational performance. J. Bus. Ethics 88 (2), 263–286.
Frank, B., 2012. The formation of consumer attitudes and intentions towards fast food restaurants. Manag. Serv. Qual. 22 (3), 260–282.
Frank, B., 2018. Consumer perceptions of the social and environmental sustainability of robotic vehicles. Global Environmental Studies 13, 113–117.
Frank, B., Enkawa, T., Schvaneveldt, S.J., 2014. How do the success factors driving repurchase intent differ between male and female customers? J. Acad. Market. Sci. 42 (2), 171–185.
Frank, B., Enkawa, T., Schvaneveldt, S.J., Herbas Torrico, B., 2015. Antecedents and consequences of innate willingness to pay for innovations: understanding motivations and consumer preferences of prospective early adopters. Technol. Forecast. Soc. Change 99, 252–266.
Gerhardt, N., 2020. 14 Robots You Need to Clean Your House. Family Handyman, Eagan, MN. https://www.familyhandyman.com/cleaning/robots-that-clean-your-house/.
Gowan, J., 2017, April 17. Pollution-eating Robots Could Help Protect the Planet. Permaculture Research Institute, The Channon, NSW, Australia. https://www.permaculturenews.org/2017/04/17/pollution-eating-robots-help-protect-planet/.
Gray, R., 2019, May 29. ORCA: China's River Cleaning Robot. Dyson On, Malmesbury, UK. https://medium.com/dyson-on/orca-chinas-river-cleaning-robot-929ce62269c4.
Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2010. Multivariate Data Analysis, seventh ed. Pearson, Upper Saddle River, NJ.
Herbas Torrico, B., Frank, B., Tavera, C.A., 2018. Corporate social responsibility in Bolivia: meanings and consequences. Int. J. Corp. Soc. Responsib. 3 (7), 1–13.
Holmes, J., 2013. Women, Men and Politeness. Routledge, New York.
Hu, Y., Frank, B., 2019, December 2-4. Green purchasing mechanisms: pollution, salience, and values. In: Proceedings of the ANZMAC 2019 Conference. Wellington.
Hughes, M.E., Waite, L.J., Hawkley, L.C., Cacioppo, J.T., 2004. A short scale for measuring loneliness in large surveys: results from two population-based studies. Res. Aging 26 (6), 655–672.
Kaab, A., Sharifi, M., Mobli, H., Nabavi-Pelesaraei, A., Chau, K.W., 2019. Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. Sci. Total Environ. 664, 1005–1019.
Kak, S., 2018, February 7. Will Robots Take Your Job? Humans Ignore the Coming AI Revolution at Their Peril. NBC News, New York, NY. https://www.nbcnews.com/think/opinion/will-robots-take-your-job-humans-ignore-coming-ai-revolution-ncna845366.
Knobloch, C., 2020. 9 Robots that Will Do Your Chores. Scripps Networks, Knoxville, TN. https://www.hgtv.com/design/remodel/products/9-robots-that-will-do-your-chores-pictures.
Koller, M., Floh, A., Zauner, A., 2011. Further insights into perceived value and consumer loyalty: a "green" perspective. Psychol. Market. 28 (12), 1154–1176.
Lee, K., 2009. Gender differences in Hong Kong adolescent consumers' green purchasing behavior. J. Consum. Market. 26 (2), 87–96.
Lindell, M.K., Whitney, D.J., 2001. Accounting for common method variance in cross-sectional research designs. J. Appl. Psychol. 86 (1), 114–121.
Liobikienė, G., Mandravickaitė, J., Bernatonienė, J., 2016. Theory of planned behavior approach to understand the green purchasing behavior in the EU: a cross-cultural study. Ecol. Econ. 125, 38–46.
Martínez, P., Del Bosque, I.R., 2013. CSR and customer loyalty: the roles of trust, customer identification with the company and satisfaction. Int. J. Hospit. Manag. 35, 89–99.
Massachusetts Institute of Technology, 2010. A swarm of robots to clean up oil spills. PLAN, vol. 77. Cambridge, MA. https://sap.mit.edu/article/standard/swarm-robots-clean-oil-spills.
Mostafa, M.M., 2007. Gender differences in Egyptian consumers' green purchase behaviour: the effects of environmental knowledge, concern and attitude. Int. J. Consum. Stud. 31 (3), 220–229.
Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S.S., Hosseinzadeh-Bandbafha, H., Chau, K.W., 2019. Comprehensive model of energy, environmental impacts and economic in rice milling factories by coupling adaptive neuro-fuzzy inference system and life cycle assessment. J. Clean. Prod. 217, 742–756.
Najafi, B., Faizollahzadeh Ardabili, S., Shamshirband, S., Chau, K.W., Rabczuk, T., 2018. Application of ANNs, ANFIS and RSM to estimating and optimizing the parameters that affect the yield and cost of biodiesel production. Engineering Applications of Computational Fluid Mechanics 12 (1), 611–624.
Nilashi, M., Rupani, P.F., Rupani, M.M., Kamyab, H., Shao, W., Ahmadi, H., Rashid, T.A., Aljojo, N., 2019. Measuring sustainability through ecological sustainability and human sustainability: a machine learning approach. J. Clean. Prod. 240, 118162.
Nižetić, S., Djilali, N., Papadopoulos, A., Rodrigues, J.J., 2019. Smart technologies for promotion of energy efficiency, utilization of sustainable resources and waste management. J. Clean. Prod. 231, 565–591.
Nosratabadi, S., Mosavi, A., Shamshirband, S., Kazimieras Zavadskas, E., Rakotonirainy, A., Chau, K.W., 2019. Sustainable business models: a review. Sustainability 11 (6), 1663.
Nyilasy, G., Gangadharbatla, H., Paladino, A., 2014. Perceived greenwashing: the interactive effects of green advertising and corporate environmental performance on consumer reactions. J. Bus. Ethics 125 (4), 693–707.
Ottman, J.A., 2011. The New Rules of Green Marketing: Strategies, Tools, and Inspiration for Sustainable Branding. Berrett-Koehler Publishers, San Francisco, CA.
Peters, A., 2019, October 26. The Ocean Cleanup Project Is Now Cleaning Plastic Out of Rivers to Stop it from Getting to the Ocean. Fast Company, New York. https://www.fastcompany.com/90422403/the-ocean-cleanup-project-is-now-cleaning-plastic-out-of-rivers-before-it-gets-to-the-ocean.
Polverino, G., Karakaya, M., Spinello, C., Soman, V.R., Porfiri, M., 2019. Behavioural and life-history responses of mosquitofish to biologically inspired and interactive robotic predators. J. R. Soc. Interface 16 (158), 2019, 0359.
Poole, D.L., Mackworth, A.K., Goebel, R., 1998. Computational Intelligence: A Logical Approach, vol. 1. Oxford University Press, New York.
Reese, B., 2019, January 1. AI Will Create Millions More Jobs than it Will Destroy: Here's How. Singularity Hub, Santa Clara, CA. https://singularityhub.com/2019/01/01/ai-will-create-millions-more-jobs-than-it-will-destroy-heres-how.
Rizk, H., Habib, M.K., 2018, October. Robotized early plant health monitoring system. Annual Conference of the IEEE Industrial Electronics Society 44, 3795–3800.
Russell, S.J., Norvig, P., 2009. Artificial Intelligence: A Modern Approach, third ed. Prentice Hall, Upper Saddle River, NJ.
Schwartz, S.H., Rubel, T., 2005. Sex differences in value priorities: cross-cultural and multimethod studies. J. Pers. Soc. Psychol. 89 (6), 1010–1028.
Sen, S., Bhattacharya, C.B., Korschun, D., 2006. The role of corporate social responsibility in strengthening multiple stakeholder relationships: a field experiment. J. Acad. Market. Sci. 34 (2), 158–166.
Sorrel, C., 2009, October 16. Scarab: a Roomba for the Mean City Streets. Wired, Boone, IA. https://www.wired.com/2009/10/scarab-a-roomba-for-the-mean-city-streets.
Spence, M., 2002. Signaling in retrospect and the informational structure of markets. Am. Econ. Rev. 92 (3), 434–459.
Sudbury Riley, L., Kohlbacher, F., Hofmeister, A., 2012. A cross-cultural analysis of pro-environmental consumer behaviour among seniors. J. Market. Manag. 28 (3–4), 290–312.
Tanner, C., Kaiser, F.G., Wölfing Kast, S., 2004. Contextual conditions of ecological consumerism: a food-purchasing survey. Environ. Behav. 36 (1), 94–111.
Tussyadiah, I.P., Park, S., 2018. Consumer evaluation of hotel service robots. In: Stangl, B., Pesonen, J. (Eds.), Information and Communication Technologies in Tourism 2018. Springer, Cham, Switzerland, pp. 308–320.
Uçar, E., Le Dain, M.A., Joly, I., 2020. Digital technologies in circular economy transition: evidence from case studies. Procedia CIRP 90, 133–136.
Vainio, A., 2019. How consumers of meat-based and plant-based diets attend to scientific and commercial information sources: eating motives, the need for cognition and ability to evaluate information. Appetite 138, 72–79.
Wang, J., Wang, S., Xue, H., Wang, Y., Li, J., 2018. Green image and consumers' word-of-mouth intention in the green hotel industry: the moderating effect of Millennials. J. Clean. Prod. 181, 426–436.
Winston, R., 2011. Human Instinct. Random House, London.
Wong, J.C., 2016, September 29. 'This Is Awful': Robot Can Keep Children Occupied for Hours without Supervision. The Guardian. https://www.theguardian.com/technology/2016/sep/29/ipal-robot-childcare-robobusiness-san-jose.
Xu, B., Lin, B., 2016. Regional differences of pollution emissions in China:

contributing factors and mitigation strategies. J. Clean. Prod. 112, 1454–1463.
Yang, C.M., 2018. Effects of message strategy and need for cognition (NFC) on consumer attitudes: a case of corporate social responsibility (CSR) advertising. Open J. Bus. Manag. 6 (3), 714–732.
Zeithaml, V.A., 1988. Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. J. Market. 52 (3), 2–22.

Further reading

Chiou, J.S., 2003. The impact of country of origin on pretrial and posttrial product evaluations: the moderating effect of consumer expertise. Psychol. Market. 20 (10), 935–954.
Dragomir, V.D., 2018. How do we measure corporate environmental performance? A critical review. J. Clean. Prod. 196, 1124–1157.
Jasch, C., 2000. Environmental performance evaluation and indicators. J. Clean. Prod. 8 (1), 79–88.
Jawahir, I.S., Dillon, O.W., Rouch, K.E., Joshi, K.J., Venkatachalam, A., Jaafar, I.H., 2006, September 11-15. Total life-cycle considerations in product design for sustainability: a framework for comprehensive evaluation. In: Proceedings of the 10th International Research/Expert Conference on Trends in the Development of Machinery and Associated Technology, Barcelona, Spain, pp. 1–10.
Pelletier, L.G., Legault, L.R., Tuson, K.M., 1996. The environmental satisfaction scale: a measure of satisfaction with local environmental conditions and government environmental policies. Environ. Behav. 28 (1), 5–26.
Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425–478.
Venkatesh, V., Thong, J.Y., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 36 (1), 157–178.