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Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The "Word-of-Machine" Effect

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Abstract

Rapid development and adoption of AI, machine learning, and natural language processing applications challenge managers and policy makers to harness these transformative technologies. In this context, the authors provide evidence of a novel "word-of-machine" effect, the phenomenon by which utilitarian/hedonic attribute trade-offs determine preference for, or resistance to, AI-based recommendations compared with traditional word of mouth, or human-based recommendations. The word-of-machine effect stems from a lay belief that AI recommenders are more competent than human recommenders in the utilitarian realm and less competent than human recommenders in the hedonic realm. As a consequence, importance or salience of utilitarian attributes determine preference for AI recommenders over human ones, and importance or salience of hedonic attributes determine resistance to AI recommenders over human ones (Studies 1–4). The word-of machine effect is robust to attribute complexity, number of options considered, and transaction costs. The word-of-machine effect reverses for utilitarian goals if a recommendation needs matching to a person's unique preferences (Study 5) and is eliminated in the case of human–AI hybrid decision making (i.e., augmented rather than artificial intelligence; Study 6). An intervention based on the consider-the-opposite protocol attenuates the word-of-machine effect (Studies 7a–b).

Keywords

algorithms, artificial intelligence, augmented intelligence, hedonic and utilitarian consumption, recommendations, technology

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Recommendations driven by artificial intelligence (AI) are pervasive in today's marketplace. Ten years ago, Amazon introduced its innovative item-based collaborative filtering algorithm, which generates recommendations by scanning through a person's past purchased or rated items and pairing them to similar items. Since then, more and more companies are leveraging advances in AI, machine learning, and natural language processing capabilities to provide relevant and in-the-moment recommendations. For example, Netflix and Spotify use AI and deep learning to monitor a user's choices and provide recommendations of movies or music. Beauty brands such as Proven, Curology, and Function of Beauty use AI to make recommendations about skincare, haircare, and makeup. Real estate services such as OJO Labs, REX Real Estate, and Roof.ai have replaced human real estate agents with chatbots powered by AI. AI-driven recommendations are also pervading the public sector. For example, the New York City Department of Social Services uses AI to give citizens recommendations about disability benefits, food assistance, and health insurance.

In response to the proliferation of AI-enabled recommendations and building on long-standing research on actuarial judgments (Dawes 1979; Groove and Meehl 1996; Meehl 1954), recent marketing research has focused on whether consumers will be receptive to algorithmic advice in various domains (Castelo, Bos, and Lehman 2019; Dietvorst, Simmons, and Massey 2014; Leung, Paolacci, and Puntoni 2019; Logg, Minson, and Moore 2019; Longoni, Bonezzi, and Morewedge 2019). However, no prior empirical investigation has systematically explored if hedonic/utilitarian trade-offs in decision making determine preference for, or resistance to, AI-based (vs. human-based) recommendations.

We focus our investigation on hedonic/utilitarian attribute trade-offs because of their influence on both consumer choice and attitudes (Bhargave, Chakravarti, and Guha 2015;

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Crowley, Spangenberg, and Hughes 1991). Specifically, we examine when and why hedonic/utilitarian attribute trade-offs in decision making influence whether people prefer or resist AI recommenders. This question is of pivotal importance for managers operating in both the private and public sectors who are looking to harness the potential of AI-driven recommendations.

Across nine studies and using a broad array of both attitudinal and behavioral measures, we provide evidence of a "word-of-machine" effect. We define "word of machine" as the phenomenon by which hedonic/utilitarian attribute trade-offs determine preference for, or resistance to, AI-based recommendations compared with traditional word of mouth, or human-based recommendations. We suggest that the word-of-machine effect stems from a lay belief about differential competence perceptions regarding AI and human recommenders. Specifically, we show that people believe AI recommenders are more competent than human recommenders to assess utilitarian attribute value and generate utilitarian-focused recommendations. By contrast, people believe that AI recommenders are less competent than human recommenders to assess hedonic attribute value and generate hedonic-focused recommendations. As a consequence, and as compared with human recommenders, individuals are more (less) likely to choose AI recommenders when utilitarian (hedonic) attributes are important or salient, such as when a utilitarian (hedonic) goal is activated.

Our research is both theoretically novel and substantively impactful. A first set of theoretical contributions relates to research on the psychology of automation and on human–technology interaction (Dawes 1979; Groove and Meehl 1996; Meehl 1954). The pervasiveness of AI-driven recommendations has led to a burgeoning body of research examining whether consumers are receptive to the advice of algorithms, statistical models, and artificial intelligence (Dietvorst, Simmons, and Massey 2014; Leung, Paolacci, and Puntoni 2019; Longoni, Bonezzi, and Morewedge 2019). With respect to this literature, we make three novel contributions. First, we extend it by addressing the previously unexplored question of when and why hedonic/utilitarian trade-offs in decision making influence preference for or resistance to AI recommenders. Second, we show under what circumstances AI-driven recommendations are preferred to, and therefore more effective, than human ones: when utilitarian attributes are relatively more important or salient than hedonic ones. These results are especially noteworthy, as most research in this area has documented a robust and generalized resistance to algorithmic advice (for exceptions, see Castelo, Bos, and Lehman 2019; Dietvorst, Simmons, and Massey 2016; Logg, Minson, and Moore 2019). Third, we explore under what circumstances consumers will be amenable to AI recommenders in the context of human–AI partnerships: when AI supports rather than replaces a human. These results are also novel as researchers have just begun devising AI systems capable of deciding when to defer (vs. not defer) to a human (Hao 2020), and empirical investigations are yet to examine if consumers will embrace such hybrid human–AI decision making.

Our research makes a second theoretical contribution to the literature on hedonic and utilitarian consumption (Alba and Williams 2013; Khan and Dhar 2010; Moreau and Herd 2009; Whitley, Trudel, and Kurt 2018). Prior research in this area has examined how the evaluation of hedonic and utilitarian products depends on characteristics of the task, locus of choice, and justifiability of choice (e.g., Bazerman, Tenbrunsel, and Wade-Benzoni 1998; Botti and McGill 2011; Okada 2005). However, research in this area has not addressed the question of whether shifts in hedonic/utilitarian trade-offs in decision making determine preference for the source of a recommendation (e.g., an AI vs. a human recommender). Recent developments of AI have brought this question to the fore, making it of critical importance for companies seeking to leverage the potential of AI-driven recommendations.

From a managerial perspective, our results are useful for companies in both the private and public sectors that are looking to leverage AI recommenders to better reach their customers. As we investigate when consumers prefer AI over human recommenders, our findings are useful for companies debating if and how to effectively leverage AI-based recommendation systems. Our findings have implications for a host of marketing decisions. For instance, our results indicate that a shift away from hedonic attributes and toward utilitarian attributes leads to consumers preferring AI recommenders. Accordingly, AI recommenders may be more aligned with functional positioning strategies than experiential ones. In addition, emphasizing utilitarian benefits may be relatively more impactful with an AI-based system than emphasizing hedonic benefits. Taken together, our research and findings provide actionable insights for managers looking for ways to leverage AI to orchestrate consumer journeys so as to successfully move customers through the funnel, increase the likelihood of successful transactions, and, overall, optimize the customer experience at each phase of the journey.

Theoretical Development

Hedonic and Utilitarian Consumption

Although consumption involves both hedonic and utilitarian considerations, consumers tend to view products as either predominantly hedonic or utilitarian (for a review, see Khan, Dhar, and Wertenbroch 2005). Hedonic consumption is primarily affectively driven, based on sensory or experiential pleasure, reflects affective benefits, and is assessed on the basis of the degree to which a product is rewarding in itself (Botti and McGill 2011; Crowley, Spangenberg, and Hughes 1991; Holbrook 1994). Utilitarian consumption is instead more cognitively driven, based on functional and instrumental goals, reflects functional benefits, and is assessed on the basis of the degree to which a product is a means to an end (Botti and

McGill 2011; Crowley, Spangenberg, and Hughes 1991; Holbrook 1994).

Prior research on hedonic/utilitarian consumption has focused on the effect of characteristics of the task on product judgments. For instance, choice tasks tend to favor utilitarian options, whereas rating tasks tend to favor hedonic options (Bazerman, Tenbrunsel, and Wade-Benzoni 1998; Okada 2005), and forfeiture increases the relative salience of hedonic attributes compared to acquisition (Dhar and Wertenbroch 2000). Justifiability leads people to assign greater weight to utilitarian (vs. hedonic) options (Okada 2005), and hedonic (vs. utilitarian) choices are associated with greater perceived personal causality (Botti and McGill 2011).

Although spanning over a decade, research on hedonic/utilitarian consumption has not yet addressed the question of whether hedonic and utilitarian trade-offs influence preference for the source of a recommendation (AI vs. human). This question has come to the fore given its importance for managers looking to leverage the potential of algorithmic recommendations. We discuss prior research on algorithmic recommendations in the next section.

(Resistance to) Algorithmic Recommendations

Ever since seminal work on statistical and actuarial predictive models was published (Dawes 1979; Grove and Meehl 1996; Meehl 1954), a large body of research has documented how statistical/actuarial models outperform clinical/human judgments in predicting a host of events, such as students' and employees' performance (Dawes 1979) and market demand (Sanders and Manrodt 2003). Despite the superior accuracy of algorithmic models, people tend to eschew them. With only a few exceptions (Castelo, Bos, and Lehman 2019; Dietvorst, Simmons, and Massey 2016; Logg, Minson, and Moore 2019), most of the extant literature has shown that people resist the advice of a statistical algorithm. For instance, recent research in the medical domain has shown that consumers may be more reluctant to utilize medical care delivered by AI providers than by comparable human providers (Longoni, Bonezzi, and Morewedge 2019; 2020). Corporate settings show similar patterns, with recruiters (Highhouse 2008) and auditors (Boatsman, Moeckel, and Pei 1997) trusting their judgment and predictions more than algorithms.

There are numerous reasons why people resist algorithmic recommendations. People (erroneously) believe that algorithms are unable to learn and improve (Dawes 1979, Highhouse 2008) and therefore lose confidence in algorithms when they see them err (Dietvorst, Simmons, and Massey 2014). People also believe that algorithms assume the world to be orderly, rigid, and stable and therefore cannot take into consideration uncertainty (Grove and Meehl 1996) and a person's uniqueness (Longoni, Bonezzi, and Morewedge 2019). Resistance to algorithmic advice may also be borne out of generalized concerns, such as people's fear of being reduced to "mere numbers" (Dawes 1979) and mistrust of algorithms' lack of empathy (Grove and Meehl 1996).

We extend this literature and show circumstances under which people prefer (and not just resist) algorithmic recommendations. Specifically, we examine how and why hedonic/utilitarian trade-offs determine preference for, or resistance to, AI recommenders, as articulated in the next section.

The Word-of-Machine Effect: Utilitarian/Hedonic Trade-offs Determine Preference for (or Resistance to) AI Recommenders

We hypothesize a word-of-machine effect, whereby hedonic and utilitarian trade-offs determine preference for or resistance to AI recommenders compared to human ones. We suggest that the word-of-machine effect stems from consumers' differing competence perceptions of AI and human recommenders in assessing attribute value and generating recommendations. Specifically, we suggest that people believe AI recommenders to be more (less) competent to assess utilitarian (hedonic) attribute value and generate utilitarian-focused (hedonic-focused) recommendations than human recommenders.

These predictions rest on the assumption that people believe hedonic and utilitarian attribute value assessment to require different evaluation competences. Hedonic value assessment should map onto criteria on the basis of experiential, emotional, and sensory evaluative dimensions. By contrast, utilitarian value assessment should map onto criteria on the basis of factual, rational, and logical evaluative dimensions. This assumption is rooted in the very definition of hedonic and utilitarian value. Hedonic value is conceptualized as reflecting experiential affect associated with a product, sensory enjoyment, and emotions (Batra and Ahtola 1991; Hirschman and Holbrook 1982). Indeed, hedonic consumption tends to be affectively rich and emotionally driven (Botti and McGill 2011). By contrast, utilitarian value is conceptualized as reflecting instrumentality, functionality, nonsensory attributes, and rationality (Batra and Ahtola 1991; Hirschman and Holbrook 1982). Overall, utilitarian consumption is cognitively driven (Botti and McGill 2011).

How do different types of recommenders (AI vs. human) then fare with respect to assessing hedonic and utilitarian attribute value? We suggest that people believe AI recommenders are more competent to assess utilitarian attribute value than human recommenders and less competent to assess hedonic attribute value than human recommenders. We attribute this lay belief to differing associations people have about how AI (vs. human) recommenders process and evaluate information. Lay beliefs are developed either directly through personal experience (Ross and Nisbett 1991) or indirectly from the environment (Morris, Menon, and Ames 2001). Throughout childhood we learn firsthand that, as humans, we are able to perceive and connect with the outside world through our affective experiences. By contrast, we learn that AI, computers, and robots are rational and logical, and lack the ability to have affective, experiential interactions with the world. These associations are reflected in idioms such as "thinking like a robot," which refers to thinking logically without taking into consideration more "human" aspects of a situation such as sensations and emotions. Thus, whereas AI and computers are associated with rationality and logic, humans are associated with emotions and experiential abilities. These associations are also echoed in books, songs, and movies. For example, in the *Star Trek* universe, the artificially intelligent form of life named Data has superior intellective abilities but is unable to experience emotions. Popular movies like *Her*, *Ex Machina*, and *Terminator* further reinforce these associations.

Accordingly, we suggest that people believe AI recommenders are more competent than human recommenders when assessing information because they use criteria that rely relatively more on facts, rationality, logic, and, overall, cognitive evaluative dimensions. By contrast, we propose that people believe human recommenders are more competent than AI recommenders when assessing information because they use criteria that rely relatively more on sensory experience, emotions, intuition, and, overall, affective evaluative dimensions.

Because people perceive AI and humans to have different competency levels when assessing information, and because assessment of utilitarian and hedonic attribute value underscore different evaluative foci, it follows that people perceive AI and humans to have different competency levels with respect to assessing utilitarian and hedonic attributes. This lay belief about competence perceptions forms the basis for the proposed word-of-machine effect. In summary, we predict that if utilitarian (hedonic) attributes are more important or salient, such as when a utilitarian (hedonic) goal is activated, people will be more (less) likely to choose AI recommenders than human recommenders.

A final note warrants mention. As competence perceptions driving the word-of-machine effect are based on a lay belief, they are embedded in the cultural context. That is, humans are not necessarily less competent than AI at assessing and evaluating utilitarian attributes. Vice versa, AI is not necessarily less competent than humans at assessing and evaluating hedonic attributes. Indeed, AI selects flower arrangements for 1-800-Flowers and creates new flavors for food companies such as McCormick, Starbucks, and Coca-Cola (Venkatesan and Lecinski 2020).

Overview of Studies

Studies 1a–b focus on product choice in field settings and show the main word-of-machine effect: that AI (human) recommenders lead to greater choice likelihood when a utilitarian (hedonic) goal is activated. Study 2 shows different perceptions that result from the two recommendation sources: AI (human) recommenders lead to higher evaluation of utilitarian (hedonic) attributes upon consumption. Study 3 shows that when a utilitarian (hedonic) attribute is considered important, consumers prefer AI (human) recommenders. Study 4 uses an analysis of mediation to corroborate the role of competence perceptions in explaining the word-of-machine effect while ruling out attribute complexity as alternative explanation. Studies 5–7 explore the scope of the word-of-machine effect by identifying boundary conditions. Study 5 shows that the effect is reversed for utilitarian goals when the recommendation needs to match to a person's unique preferences, a type of task people view AI as unfit to do. Study 6 shows that the effect is eliminated when AI is framed as "augmented" intelligence rather than artificial intelligence, that is, when AI enhances and supports a person rather than replacing them. Finally, Studies 7a–b test an intervention using the consider-the-opposite protocol to moderate the word-of-machine effect.

Studies 1a–b: Preference for AI Recommenders When Utilitarian Goals Are Activated

Studies 1a–b focus on the word-of-machine effect on actual product choice in field settings as a function of an activated utilitarian or hedonic goal. We first activated either a utilitarian or a hedonic goal and then, in an incentive-compatible setting, measured choice as a function of recommender.

Study 1a: Hair Treatment Sample

Procedure. Two hundred passersby in a city in northeast United States participated in Study 1a on a voluntary basis. We handed willing passersby a leaflet explaining that we were conducting a blind test for products in the haircare industry and, specifically, for hair masks—a leave-in treatment for hair and scalp. Passersby read that for the purpose of the market test, we wanted them to select one of two hair mask samples solely on the basis of the instructions in the leaflet. These instructions activated, in a two-cell between-subjects design, either a hedonic or a utilitarian goal:

> [Hedonic] For the purpose of this blind test, it is very important that you set aside all thoughts you might already have about hair masks. Instead, we would like you to focus only on the following. Imagine that you have a "hedonic" goal. We would like you to imagine that the only things that you care about in a hair mask are hedonic characteristics, like how indulgent it is to use, its scent, and the spa-like vibe it gives you. When you make the next choice, imagine that there are no other things that are important for you in a hair mask.

> [Utilitarian] For the purpose of this blind test, it is very important that you set aside all thoughts you might already have about hair masks. Instead, we would like you to focus only on the following. Imagine that you have a "utilitarian" goal. We would like you to imagine that the only things that you care about in a hair mask are utilitarian characteristics, like how practical it is to use, its objective performance, and the chemical composition. When you make the next choice, imagine that there are no other things that are important for you in a hair mask.

The leaflet further explained that there were two hair mask options from which they could choose. One option had been recommended by a person, and the other option had been recommended by an algorithm. The leaflet specified that the person and the algorithm had the same haircare expertise and that the pots of hair masks, available for pickup on a desk, all contained the same amount of fluid ounces. The pots were identical except for a marking of "P" if selected by a person or "A" if selected by an algorithm (stimuli in Web Appendix A). The key dependent variable was whether passersby chose the product selected by the person or by the algorithm.

Results and discussion. To assess product choice, we compared the proportion of people who chose the product recommended by the algorithm with the proportion of people who chose the product recommended by the person depending on the activated goal (utilitarian vs. hedonic). The two proportions differed significantly ($\chi^2(1, N = 200) = 12.60$, $p = .001$). As predicted, when a utilitarian goal was activated, more people chose the product recommended by the algorithm (67%) than by the person (33%; $z = 4.81$, $p < .001$). When a hedonic goal was activated, more people chose the product recommended by the person (58%) than by the algorithm (42%; $z = 2.26$, $p = .024$).

Study 1b: Selection of House Properties

Procedure. Study 1b was a field study conducted over four consecutive days in Cortina, a resort town in northeast Italy. We selected this town because in 2026 it will host the Olympic games and is likely to experience a boom in its real estate market, which is the domain of the study. We secured the use of a centrally located bar and set up the study as follows. We placed an ad (translated to Italian) promoting a local real estate agency at the bar entrance. The ad headline reminded people of the opportunity to make fruitful real estate investments due to the upcoming Olympic games. In a two-cell, between-subjects design, we alternated the text in the ad to focus people on a hedonic or utilitarian goal:

> [Hedonic] With the Olympic games coming up, it is really important that you look for a real estate investment that is fun, enjoyable, and speaks to your emotions. You want a place that pleases your senses considering all the changes that will affect [name of town] in the next few years.

> [Utilitarian] With the Olympic games coming up, it is really important that you look for a real estate investment that is functional, useful, and speaks to your rationality. You want a place that is practical considering all the changes that will affect [name of town] in the next few years.

At the bottom of the ad there were two envelopes described as containing a curated selection of available properties in Cortina that could fit with the opportunity in the ad (i.e., one of the activated goals). One property selection had been (ostensibly) curated by a person (the respective envelope read: "one of [name of agency]'s agents has selected these properties") and the other by an algorithm (the respective envelope read: "[name of agency]'s proprietary algorithm has selected these properties"). The ad invited people to pick up only one of the two envelopes given the limited quantity of promotional materials (stimuli in Web Appendix B). The key dependent variable was whether people chose the selection made by the agent or by the algorithm. A waiter ensured that participants took only one of the two envelopes, and we excluded two participants who picked up two (final N = 229).

Results and discussion. We compared the proportion of people who chose the selection made by the algorithm with the proportion of people who chose the selection made by the agent depending on the activated goal (utilitarian vs. hedonic). The two proportions differed significantly ($\chi^2(1, N = 229) = 29.33$, $p < .001$). When the goal was utilitarian, more people chose the selection made by the algorithm (59.8%) than by the agent (40.2%; $z = 3.07$, $p = .002$), whereas when the goal was hedonic, more people chose the selection made by the agent (75.7%) than by the algorithm (24.3%; $z = 7.52$, $p < .001$).

Together, Studies 1a–b show that when a utilitarian goal is activated, people are more likely to choose an AI recommender than a human recommender. When a hedonic goal is activated, people are less likely to choose an AI recommender than a human recommender.

Study 2: AI Recommenders Shift Hedonic/ Utilitarian Perceptions Upon Consumption

Study 2 examines the word-of-machine effect upon consumption. As conceptual information such as expectations affects food consumption experiences (e.g., Allison and Uhl 1964; Wardle and Solomons 1994), we predicted that the type of recommender would affect perceptions of hedonic and utilitarian attributes upon actual consumption of a product (a chocolate cake).

Procedure

One hundred forty-four participants from a paid subject pool (open to students and nonstudents) at the University of Virginia completed this study ($M_{age} = 27.5$ years, $SD = 9.5$; 60.4% female). We told participants that we were testing chocolate cake recipes on behalf of a local bakery (stimuli in Web Appendix C). We told participants that the bakery had two options for chocolate cake recipes: one created using the ingredient selection of an AI chocolatier and one created using the ingredient selection of a human chocolatier. We specified that both the human and AI chocolatier had access to the same recipe database. We invited participants to look at the two chocolate cakes on top of a podium in a pop-up bakery/classroom desk. The two types of cake looked (and were) identical. We told participants that the two chocolate cakes, although based on different recipes, looked the same because the bakery did not want them to be influenced by the shape or the color. In a two-cell between-subjects design, we asked participants to consume either the chocolate cake whose recipe was selected by the human chocolatier or the one selected by the AI chocolatier. After consuming the cake, we measured hedonic/utilitarian attribute perceptions by asking participants to rate the cake on two hedonic items (indulgent taste and aromas; pleasantness to the senses [vision, touch, smell, etc.]) and two utilitarian items (beneficial chemical properties [antioxidants]; healthiness [micro/macro nutrients, etc.]) on seven-point scales anchored at 1 = "very low" and 7 = "very high." The order of hedonic and utilitarian items was randomized.

Results and Discussion

Hedonic attribute perceptions. A one-way analysis of variance (ANOVA) on the average of the two hedonic items (r = .87, $p < .001$) revealed that, upon consumption, participants rated the chocolate cake as having lower hedonic value when based on the recommendation of an AI chocolatier than a human one ($M_{AI} = 4.57$, SD = 1.38; $M_H = 6.17$, SD = 1.03; $F(1, 142) = 61.33$, $p < .001$).

Utilitarian attribute perceptions. A one-way ANOVA on the index of the two utilitarian items (r = .84, $p < .001$) revealed that, upon consumption, participants rated the chocolate cake as having higher utilitarian value when based on the recommendation of an AI chocolatier than a human one ($M_{AI} = 5.48$, SD = 1.21; $M_H = 5.02$, SD = 1.35; $F(1, 142) = 61.33$, $p = .034$).

Thus, Study 2 shows that the word-of-machine effect extends to actual consumption and that the type of recommender influences people's perceptions of hedonic/utilitarian trade-offs. AI recommenders led participants to perceive greater utilitarian attribute value and lower hedonic attribute value compared to human recommenders.

Study 3: Preference for AI Recommenders When Utilitarian Attributes Are More Important

Study 3 further tests the word-of-machine effect. Instead of activating hedonic/utilitarian goals as in Studies 1a–b, we measured the importance given to hedonic/utilitarian attributes with respect to a specific product category (winter coats). Then, we assessed relative preference for a human or an AI recommender. We expected people to prefer AI to human recommenders when utilitarian attributes were more important to them, and to prefer human over AI recommenders when hedonic attributes were more important to them. We benchmarked these hypotheses with a condition in which people chose between two human recommenders, wherein we expected recommender preference to be uncorrelated with importance assigned to hedonic/utilitarian attributes.

Procedure

Three hundred three respondents ($M_{age} = 38.0$ years, SD = 11.1; 49.5% female) recruited on Amazon Mechanical Turk participated in exchange for monetary compensation. Participants imagined that they were planning to purchase a new winter coat (as it was the winter season) and were looking for recommendations. Participants read that winter coats have functional/utilitarian aspects ("Winter coats have functional or utilitarian aspects, such as insulating power, breathability, and the degree to which the coat is rain and wind proof") and sensory/hedonic aspects ("Winter coats have sensory or hedonic aspects, such as the color and other aesthetics, the way the fabric feels to the touch, and the degree to which the coat fits well"). Then, to measure the importance of hedonic/utilitarian attributes, participants rated the extent to which, in general, they cared about sensory/hedonic and functional/utilitarian aspects in winter coats (1 = "mostly care about functional/utilitarian aspects," and 7 = "mostly care about sensory/hedonic aspects").

Participants then read that to get recommendations about winter coats, they could rely on one of two shopping assistants, X or Y. We specified that both assistants had access to the same type and size of database, would charge the same fees, would generate recommendations autonomously, and were trained to serve users well and to the best of their capacity. To control for the possibility that different recommenders would be associated with different service quality perceptions, we also specified that the two shopping assistants had the same rating of 4.9/5.0 stars provided by 687 consumers that had used their services in the past. To manipulate choice set, half of the participants chose between two human shopping assistants (both X and Y were people and were described as two different sales associates at that particular retailer), and the other half chose between a human assistant, X, and an AI assistant, Y. Thus, whereas X was always human, Y was either human or AI depending on the condition. Finally, participants indicated their preference for one of the assistants (1 = "definitely shopping assistant X," 4 = "indifferent," and 7 = "definitely shopping assistant Y").

Results and Discussion

We regressed recommender preference on choice set (human–human vs. human–AI), hedonic/utilitarian attribute importance, and their interaction. This analysis revealed significant main effects of choice set (b = .85, $t(299) = 5.49$, $p < .001$) and hedonic/utilitarian attribute importance (b = .32, $t(299) = 7.46$, $p < .001$), as well as a significant two-way interaction (b = −.29, $t(299) = -6.91$, $p < .001$). As hedonic/utilitarian attribute importance was continuous, we explored the interaction using the Johnson–Neyman floodlight technique (Spiller et al. 2013), which revealed a significant effect of recommender preference in human–AI choice set for levels of hedonic/utilitarian attribute importance lower than 2.35 ($b_{JN} = .15$, SE = .08, $p = .050$) and higher than 3.36 ($b_{JN} = -.14$, SE = .07, $p = .050$). That is, the more participants cared about utilitarian attributes (values lower than 2.35 on the seven-point scale), the more they preferred an AI assistant over a human one. Conversely, the more participants cared about hedonic attributes (values higher than 3.36 on the seven-point scale), the more they preferred a human assistant over an AI one. As predicted, in the human–human choice set, which served as the control condition, participants were indifferent between the two assistants (M = 3.98, SD = .34) and recommender preference was uncorrelated with hedonic/utilitarian attribute importance (r = .116, $p = .162$; see Figure 1).

These results provided correlational evidence that hedonic/utilitarian attribute importance predicts preference between human and AI recommenders. The next study utilizes an

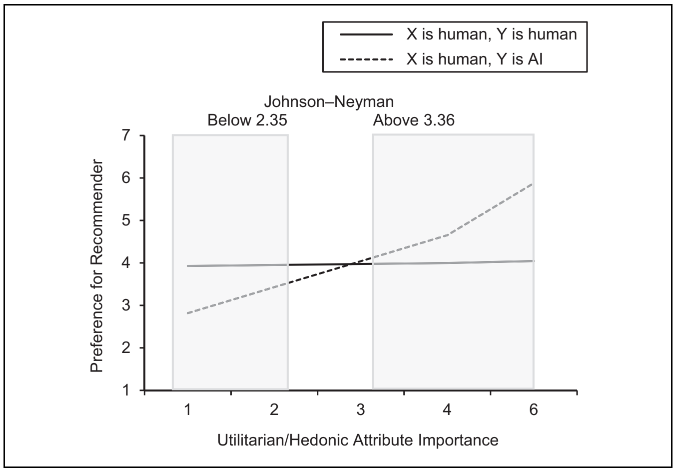

Figure 1. Results of Study 3: Preference for AI (human) recommenders when utilitarian (hedonic) attributes are more important.
Note. The y-axis represents preference for recommender measured on a seven-point scale anchored at 1 = "definitely shopping assistant X," and 7 = "definitely shopping assistant Y." The x-axis represents importance of hedonic/utilitarian attributes, measured on a seven-point scale anchored at 1 = "mostly care about functional/utilitarian aspects," and 7 = "mostly care about sensory/hedonic aspects." The shaded region represents area of significance.

analysis of mediation to test competence perceptions as drivers of the word-of-machine effect.

Study 4: Mediation by Competence Perceptions: Ruling Out Complexity

Study 4 uses an analysis of mediation to measure competence perceptions as lay beliefs underlying the word-of-machine effect. In addition, this study tests attribute complexity as an alternative explanation: a belief that AI recommenders are better capable to process more complex attribute information than human recommenders. One could argue that utilitarian attributes seem more complex to evaluate than hedonic attributes. If this argument is accurate, preference for AI recommenders when utilitarian attributes are more salient could be explained by a lay belief about the recommender's ability, higher for AI recommenders, to deal with complexity.[1] We tested this alternative explanation by manipulating attribute complexity orthogonally to recommender type (human, AI) and activated goal (hedonic, utilitarian). We manipulated attribute complexity by way of number of product attributes, which is consistent with prior research (Littrell and Miller 2001; Timmermans 1993).

Procedure

Four hundred two participants (M_{age} = 38.5 years, SD = 12.6; 46% female) from Amazon Mechanical Turk participated in exchange for monetary compensation in a 2 (complexity: low, high) × 2 (goal: hedonic, utilitarian) × 2 (recommender: human, AI) between-subjects design.

Participants read about the beta testing of a new app created to give recommendations of chocolate varieties by relying on one of two sources: a human or an AI master chocolatier (i.e., a computer algorithm). We told participants that the human and AI recommenders relied on the same database of chocolate varieties and operated autonomously. The app had the same cost regardless of recommender. Participants saw screenshots of the app (Figure 2).

We specified that the ratings of the chocolate varieties in the data set were not based on personal experience but rather that they had been rated by consumers and manufacturers in terms of certain dimensions that varied by complexity condition. In the high complexity condition, we described the chocolate varieties as being rated on eight attributes, four of which were hedonic (sensory pleasure, taste, fun factor, and pairing combinations) and four of which were utilitarian (chemical profile, nutritional index, digestibility profile, and health factor). In the low complexity condition, we described the chocolate varieties as being rated on two attributes, one of which was hedonic (sensory pleasure) and one of which was utilitarian (chemical profile).We then activated either a hedonic or a utilitarian goal by asking participants to set aside all thoughts they might already have had about chocolate and instead imagine that they wanted a recommendation based only on (1) sensory pleasure, taste, fun factor, and pairing combinations (hedonic/high complexity); (2) sensory pleasure (hedonic/low complexity); (3) chemical profile, nutritional index, digestibility profile, and health factor (utilitarian/high complexity); or (4) chemical profile (utilitarian/low complexity). Finally, we manipulated recommender in a two-cell (recommender: human, AI) between-subjects design by telling participants that in the version of the app they were considering, it was either the human or the AI master chocolatier that would give them a recommendation.

As a behavioral dependent variable, we asked participants if they wanted to download the chocolate recommendation at the end of the survey (yes, no), specifying that payment would not be conditional on electing to download the recommendation (which is consistent with previous research; see Cian, Longoni, and Krishna 2020). We then measured the hypothesized mediator (competence perceptions) by asking participants to rate the extent to which they thought the human (AI) recommender (1) was competent to recommend the type of chocolate they were looking for and (2) could do a good job recommending the type of chocolate they were looking for (1 = "strongly disagree," and 7 = "strongly agree"; r = .89, $p < .001$).[2] At the

[1] We thank the associate editor and two anonymous reviewers for this suggestion.

[2] We added manipulation checks at the end of the survey. These manipulation checks were of recommender and goal, and participants indicated the recommender (human, AI) of the app they considered and the goal they had (hedonic, utilitarian). The recommender manipulation check was answered correctly by 93.0% of the participants, and the goal manipulation check was answered correctly by 90.8% of the participants. Statistical conclusions did not differ when restricting the analysis to participants who passed either manipulation check.

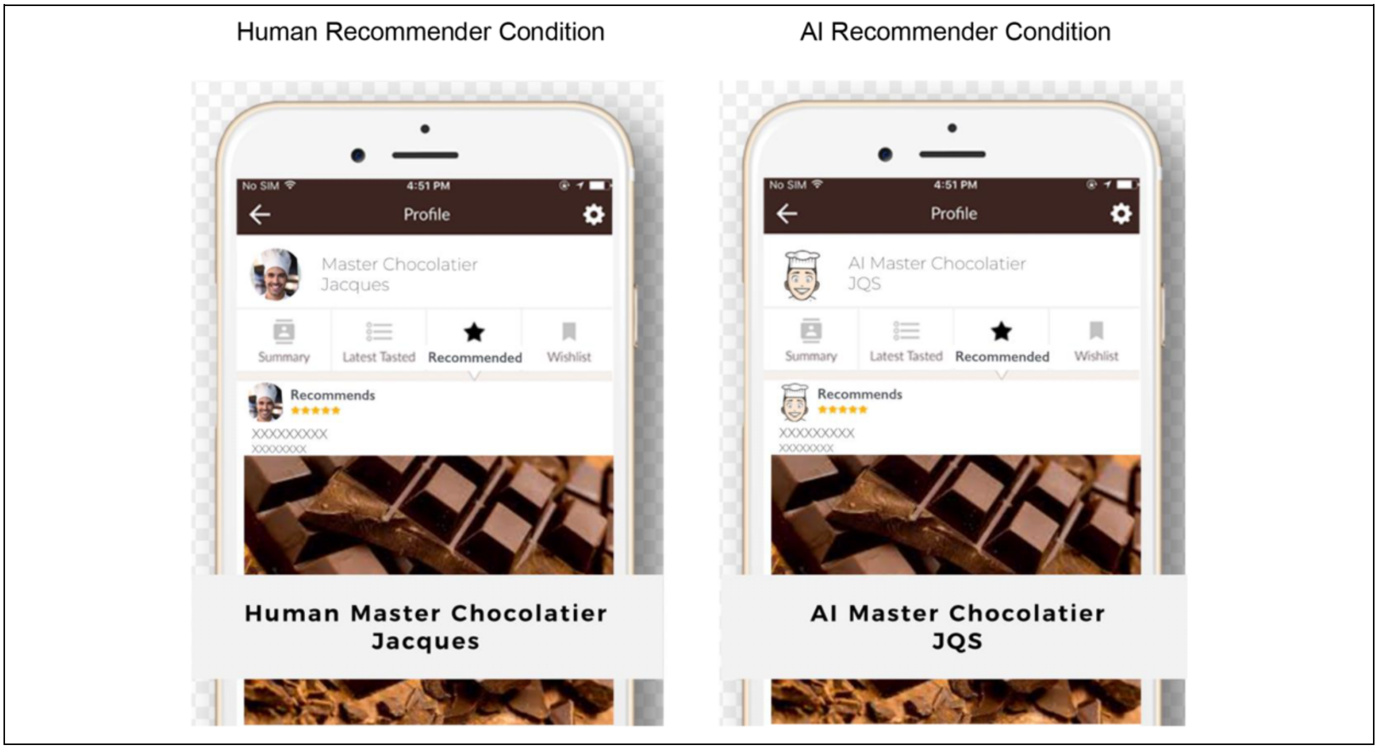

Figure 2. Stimuli of Study 4.

very end of the survey, participants who elected to download the recommendation were automatically directed to a downloadable PDF document with information about the chocolate (a relatively more indulgent hazelnut-based chocolate called "gianduiotti" in the hedonic condition or a relatively healthier chocolate toasted at low temperature called "crudista" in the utilitarian condition).

Results and Discussion

Behavior. We assessed behavior (i.e., the proportion of participants who decided to download vs. not download the recommendation) by using a logistic regression with complexity, goal, recommender, and their two-way and three-way interactions as independent variables (all contrast coded) and download (1 = yes, 0 = no) as dependent variable. We found no significant main effect of complexity (B = −.04, Wald = .09, 1 d.f., $p = .77$) or goal (B = .03, Wald = .06, 1 d.f., $p = .81$), and we found a marginally significant main effect of recommender (B = .25, Wald = 3.75, 1 d.f., $p = .053$). The three-way goal × recommender × complexity interaction was not significant (B = −.11, Wald = .80, 1 d.f., $p = .37$), ruling out the role of complexity. In terms of two-way interactions, complexity did not interact with goal (B = −.13, Wald = 1.04, 1 d.f., $p = .31$) nor with recommender (B = −.18, Wald = 1.99, 1 df, $p = .16$). Replicating previous results, the two-way goal × recommender interaction was significant (B = .75, Wald = 34.60, 1 d.f., $p < .001$). The AI recommender led to more downloads than the human recommender when the goal was utilitarian (M_{AI} = 82%, M_H = 63%; z = 3.10, $p = .002$) and fewer downloads when the goal was hedonic (M_{AI} = 52%, M_H = 88%; z = −5.63, $p < .001$).

Competence perceptions. A 2 × 2 × 2 ANOVA on competence perceptions revealed no significant main effect of complexity ($F(1, 394) = 1.24$, $p = .27$) and significant main effects of goal ($F(1, 394) = 8.99$, $p = .003$) and recommender ($F(1, 394) = 19.81$, $p < .001$). The three-way complexity × goal × recommender interaction was not significant ($F(1, 394) = .64$, $p = .44$), ruling out complexity. In terms of two-way interactions, complexity did not interact with goal ($F(1, 394) = .61$, $p = .44$), nor with recommender ($F(1, 394) = .36$, $p = .55$). Importantly, the two-way goal × recommender interaction was significant ($F(1, 394) = 57.63$, $p < .001$). Planned contrasts revealed that participants perceived the AI recommender as more competent than the human recommender in the case of a utilitarian goal ($M_{AI} = 5.92$, $SD_{AI} = 1.10$; $M_H = 5.50$, $SD_H = 1.38$; $F(1, 394) = 4.90$, $p = .027$) and less competent in the case of a hedonic goal ($M_{AI} = 4.51$, $SD_{AI} = 1.77$; $M_H = 6.13$, $SD_H = .96$; $F(1, 394) = 73.04$, $p < .001$).

Moderated mediation. We ran a moderated mediation model using PROCESS Model 8 (5,000 resamples; Hayes 2018). In this model, the moderating effect of goal takes place before the mediator (competence perceptions). The interaction between recommender and goal was significant (95% CI = .38 to .64) in the path between the independent variable and the mediator but not in the path between the independent variable and the dependent variable (95% CI = −.08 to .63). As predicted, the indirect effect recommender → competence perceptions →

download was significant but in the opposite direction conditionally on the moderator (hedonic: 95% CI = 1.19 to 2.40; utilitarian: 95% CI = −.88 to −.06).

These results provide evidence for the hypothesized role of competence perceptions as drivers of the word-of-machine effect. Participants rated AI recommenders as more (less) competent in the case of utilitarian (hedonic) goals. Differential competence perceptions explained higher choice likelihood for the AI's recommendation than the human's if a utilitarian goal had been activated and lower choice likelihood for the AI's recommendation than the human's if a hedonic goal had been activated. Furthermore, we did not find evidence that the word-of-machine effect was moderated by complexity. The next three studies tested the scope of the word-of-machine effect by identifying boundary conditions.

Study 5: Testing Unique Preference Matching as a Boundary Condition

Study 5 explores a circumstance under which the word-of-machine effect might reverse: when consumers want a recommendation that matches their unique needs and preferences.[3] Matching a recommendation to one's preferences is valued and might even be expected (Franke, Keinz, and Steger 2009). In this study, we tested the hypothesis that consumers view the task of matching a recommendation to one's unique preferences as being better performed by a person than by AI.[4] This argument is in line with recent research in the medical domain showing that consumers perceive AI as less able than a human physician to tailor a medical recommendation to their unique characteristics and circumstances (Longoni, Bonezzi, and Morewedge 2019). Thus, we expected people to choose AI recommenders at a lower rate and, conversely, choose human recommenders at a higher rate if matching to unique preferences was salient, even in the case of an activated utilitarian goal. In other words, if matching to unique preferences was salient, we expected people to prefer a human recommender for both hedonic and utilitarian goals. We tested this possibility by manipulating whether participants' desire to have a recommendation matched to their unique needs and preferences was salient and then measuring their choice of recommender.

Procedure

Five hundred forty-five respondents (M_{age} = 39.0 years, SD = 12.9; 46.6% female) from Amazon Mechanical Turk participated in exchange for monetary compensation in a 2 (goal: hedonic, utilitarian) x 2 (matching: unique preferences, control) between-subjects design. Participants read information about the beta testing of a new smartphone app offered by a real estate service. The app would allow users to chat with a Realtor to find properties to buy or rent. Participants further read that there were two versions of this app. In one version of the app, users would interact with a human Realtor, and in the other version, users would interact with an AI Realtor (i.e., a computer algorithm). Participants saw screenshots of the app (Figure 3) and read about how the app would work: the users would indicate what attributes they were looking for in a property (square footage, number of rooms, budget) and the [Realtor/AI Realtor] would use [their/its] training and knowledge to make apartment recommendations. We specified that both the human and AI Realtors had access to the same number and type of property listings. We then activated either a hedonic or a utilitarian goal by asking participants to set aside all thoughts they might already have had about apartments and instead imagine that they wanted a recommendation based only on: (1) how trendy the neighborhood is, the apartment views, aesthetics (hedonic goal condition) or (2) distance to their workplace, proximity to public transport, functionality (utilitarian goal condition; based on Bhargave, Chakravarti, and Guha 2015). Finally, to make unique preference matching salient, we told half of the participants that it was very important for them to get a recommendation that would be matched to their unique needs and personal preferences. Participants in the control condition were not focused on unique preference matching. As a dependent variable, we measured choice of recommender by asking participants if, given the circumstances described, they wanted to chat with the human or the AI Realtor.

Results and Discussion

We assessed choice on the basis of the proportion of participants who decided to chat with the human versus AI Realtor by using a logistic regression with goal, matching, and their two-way interaction as independent variables (all contrast coded) and choice (0 = human, 1 = AI) as a dependent variable. We found significant effects of goal (B = 1.75, Wald = 95.70, 1 df, $p < .000$) and matching (B = .54, Wald = 24.30, 1 df, $p < .000$). More importantly, goal interacted with matching (B = .25, Wald = 5.33, 1 df, $p = .021$). Results in the control condition (when unique preference matching was not salient) replicated prior results: in the case of an activated utilitarian goal, a greater proportion of participants chose the AI Realtor (76.8%) over the human Realtor (23.2%; z = 8.91, $p < .001$), and when a hedonic goal was activated, a lower proportion of participants chose the AI (18.8%) over the human Realtor (81.2%; z = 10.35, $p < .001$). However, making unique preference matching salient reversed the word-of-machine effect in the case of an activated utilitarian goal: choice of the AI Realtor decreased to 40.3% (from 76.8% in the control; z = 6.17, $p < .001$). That is, making unique preference matching salient turned preference for the AI Realtor into resistance despite the activated utilitarian goal, with most participants choosing the human over the AI Realtor. In the

[3] We thank an anonymous reviewer for this suggestion.

[4] We validated this hypothesis by asking respondents from Amazon Mechanical Turk (N = 95) the extent to which they would expect a property selected by [a human/an AI] Realtor to match their unique preferences and needs (1 = "not at all," and 7 = "very much"). Indeed, participants expected the human Realtor to be more able than the AI Realtor to match a property recommendation to their unique preferences and needs (M_H = 5.85, SD = 0.82, M_{AI} = 4.70, SD = 1.30; F(1, 93) = 26.69, $p < .001$).

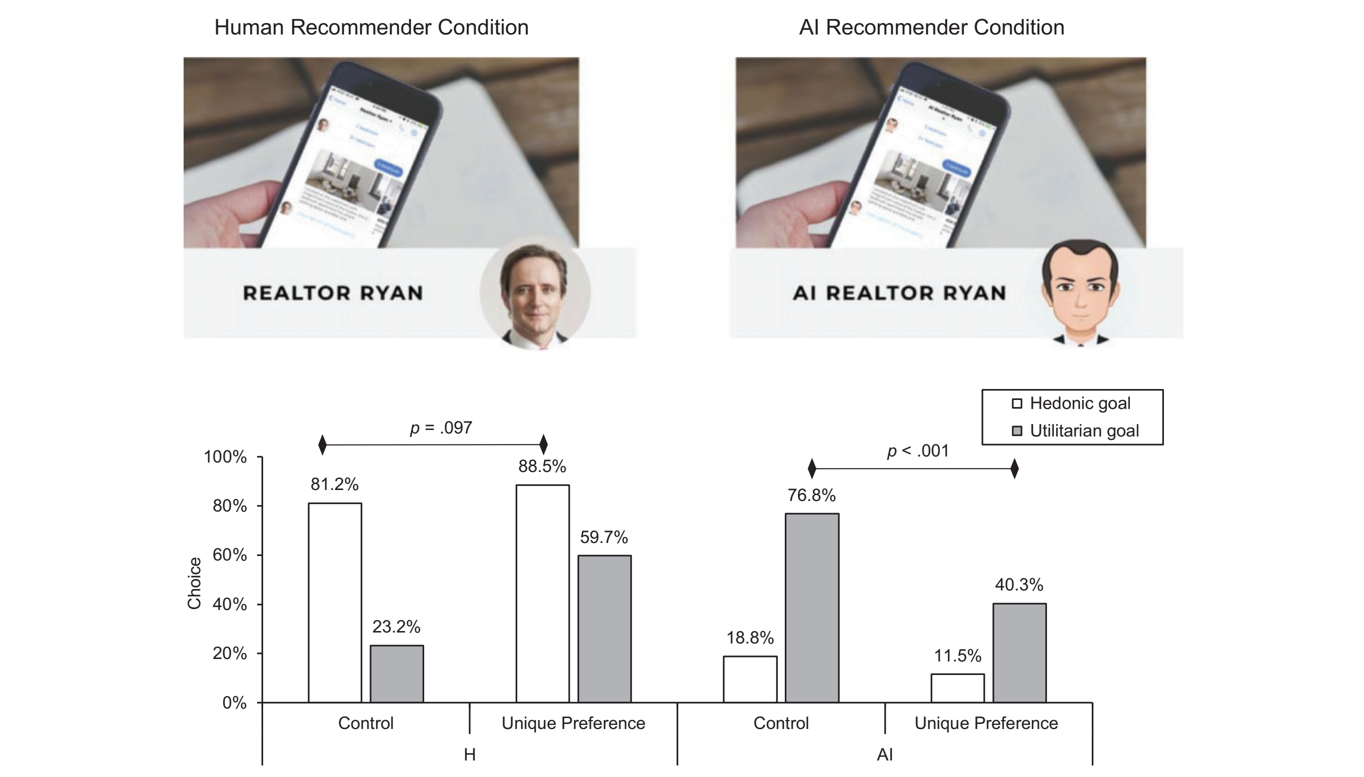

Figure 3. Stimuli (top) and results (bottom) of Study 5: The word-of-machine effect is reversed for utilitarian goals if the recommendation needed to match participants' unique preferences.

Note. The y-axis represents the proportion of participants who chose to chat with the human versus AI realtor.

case of an activated hedonic goal, making unique preference matching salient further strengthened participants' choice of the human Realtor, which increased to 88.5% from 81.2% in the control, although the effect was marginal, possibly due to a ceiling effect ($z = 1.66$, $p = .097$).

Overall, whereas the word-of-machine effect replicated in the control condition when unique preference matching was salient, participants preferred the human Realtor over the AI recommender both in the hedonic goal conditions (human = 88.5%, AI = 11.5%; $z = 12.40$, $p < .001$) and in the utilitarian goal conditions (human = 59.7%, AI = 40.3%; $z = 3.24$, $p = .001$; Figure 3), corroborating the notion that people view AI as unfit to perform the task of matching a recommendation to one's unique preferences.

These results show that preference matching is a boundary condition of the word-of-machine effect, which reversed in the case of a utilitarian goal when people had a salient goal to get recommendations matched to their unique preferences and needs. The next study tests another boundary condition.

Study 6: Testing Augmented Intelligence as a Boundary Condition

Study 6 explores under what circumstances the word-of-machine effect is eliminated, and it tests the role of AI as boundary condition. Studies 1–5 tested cases in which the role of AI was to replace human recommenders. Study 6 explores the case in which AI is leveraged to *assist* and *augment* human intelligence. "Augmented intelligence" involves AI's assistive role in enhancing and amplifying human intelligence instead of replacing it (Araya 2019). So far, we have showed that consumers resist AI recommenders when a hedonic goal is activated. In Study 6, we tested the hypothesis that consumers will be more receptive to AI recommenders, even in the case of a hedonic goal, if the AI recommender assists and amplifies a human recommender who retains the role of ultimate decision maker. In this case, we expected people to believe that the human decision maker would compensate for the AI's relative perceived incompetence in the hedonic realm. We expected the reverse effect in the case of a utilitarian goal. In other words, we expected that augmented intelligence—a human–AI hybrid decision making model— would help bolster AI to the level of humans for hedonic decision making and help bolster humans to the level of AI for utilitarian decision making. In addition, we added a control condition in Study 6 in which neither recommender was mentioned to serve as a baseline measure of participants' perceptions of hedonic and utilitarian attributes.

Procedure

Four hundred four respondents ($M_{age} = 40.2$ years, $SD = 12.5$; 48.9% female) from Amazon Mechanical Turk participated in exchange for monetary compensation in a three-cell (recommender: human, artificial intelligence, augmented intelligence) between-subjects design. A fourth control condition contained no recommender manipulation and served as the baseline.

The stimuli and procedure were identical to those of Study 4. Participants read about the beta testing of a new app created to give recommendations of chocolate varieties by relying on one of two sources: a human or an AI master chocolatier. Participants read that human and AI recommenders relied on the same database, which comprised a large number of chocolate varieties that had been rated by consumers and manufacturers. Participants read that the app had the same cost regardless of the type of recommender it relied on. Finally, participants read that the app would suggest a curated selection of five chocolate bars.

We then manipulated recommender by randomly assigning participants to (1) a human condition, in which a human chocolatier would curate the chocolate section; (2) an artificial intelligence condition, in which an AI chocolatier (i.e., a computer algorithm) would curate the chocolate section; or (3) an augmented intelligence condition, in which the AI chocolatier would assist the human chocolatier in the curation of the chocolate selection. Specifically, participants read:

> [Human condition] In the version of the app we are testing today, it is the human chocolatier that curates a selection of chocolate bars. This selection contains five chocolate bars selected by the human chocolatier. That is, it is a person who selects chocolate bars. This version of the app is technically called "human intelligence," because it uses what human intelligence can do.
>
> [Artificial intelligence condition] In the version of the app we are testing today, it is the A.I. chocolatier that curates a selection of chocolate bars. This selection contains five chocolate bars selected by the A.I. chocolatier. That is, it is a computer algorithm that selects chocolate bars. This version of the app is technically called "artificial intelligence," because it uses a computer algorithm to substitute and replace what human intelligence can do.
>
> [Augmented intelligence condition] In the version of the app we are testing today, it is the A.I. chocolatier that curates a selection of chocolate bars. This selection contains five chocolate bars selected by the A.I. chocolatier. That is, it is a computer algorithm that selects chocolate bars. The computer algorithm makes the initial selection and assists a human chocolatier, who will make the final decision about which chocolate bars to recommend. This version of the app is technically called "augmented intelligence," because it uses a computer algorithm to enhance and augment what human intelligence can do.

The control condition entailed no recommender manipulation; instead, it merely included a description of the app and no information about the source of the chocolate bar recommendation. As a dependent variable, we measured hedonic attribute perceptions with two items (indulgent taste and aromas; pleasantness to the senses [vision, touch, smell, etc.]) and utilitarian attribute perceptions with two items (beneficial chemical properties [antioxidants, etc.]; healthiness [micro/macro nutrients, etc.]), all on seven-point scales anchored at 1 = "very low," and 7 = "very high." The order of items was randomized.

Results and Discussion

Hedonic attribute perceptions. The one-way ANOVA on the average of the two items measuring hedonic attribute perceptions ($r = .79$, $p < .001$) was significant ($F(1, 436) = 48.92$, $p < .001$). In line with previous results, and replicating the word-of-machine effect, participants reported higher hedonic attribute perceptions when the recommender was human ($M_H = 6.00$; $SD = 1.06$) than when the recommender was AI ($M_{artificial\_intelligence} = 4.15$, $SD = 1.64$; $F(1, 436) = 125.55$, $p < .001$). However, when the AI recommender was augmenting human intelligence, the word-of-machine effect was eliminated: participants reported the same hedonic perceptions ($M_{augmented\_intelligence} = 5.74$, $SD = 1.11$) as they did when the recommender was human ($F(1, 436) = 2.31$, $p = .129$) and higher hedonic perceptions than when the recommender was AI alone ($F(1, 436) = 84.73$, $p < .001$). Participants in the control condition reported lower hedonic perceptions ($M_{control} = 5.62$, $SD = 1.09$) than participants in the human condition ($F(1, 436) = 5.32$, $p = .022$) and higher hedonic perceptions than participants in the AI condition ($F(1, 436) = 77.92$, $p < .001$). Control condition and augmented intelligence condition did not differ ($F(1, 436) < 1$, $p = .49$).

Utilitarian attribute perceptions. The one-way ANOVA on the average of the two items measuring utilitarian attribute perceptions ($r = .75$, $p < .001$) was significant ($F(1, 436) = 6.60$, $p < .001$). In line with previous results, and replicating the word-of-machine effect, participants reported higher utilitarian attribute perceptions when the recommender was AI ($M_{artificial\_intelligence} = 5.24$; $SD = 1.41$) than when the recommender was human ($M_H = 4.75$, $SD = 1.57$; $F(1, 436) = 6.40$, $p = .012$). However, when the AI recommender was augmenting human intelligence, the word-of-machine effect was eliminated: participants reported the same utilitarian perceptions ($M_{augmented\_intelligence} = 5.44$, $SD = 1.32$) as they did when the recommender was AI alone ($F(1, 436) = .99$, $p = .321$) and higher utilitarian perceptions than when the recommender was human ($F(1, 436) = 11.87$, $p < .001$). Participants in the control condition reported the same utilitarian perceptions ($M_{control} = 4.70$, $SD = 1.56$) as participants in the human condition ($F(1, 436) = .05$, $p = .820$) and lower utilitarian perceptions than participants in both the AI ($F(1, 436) = 7.47$, $p = .007$) and augmented intelligence conditions ($F(1, 436) = 13.22$, $p < .001$; Figure 4).

These results delineate the scope of the word-of-machine effect and show a circumstance under which the effect is eliminated. Even when a hedonic goal was activated, AI recommenders fared as well as human recommenders as long as they were in a hybrid decision-making model in partnership with a human.

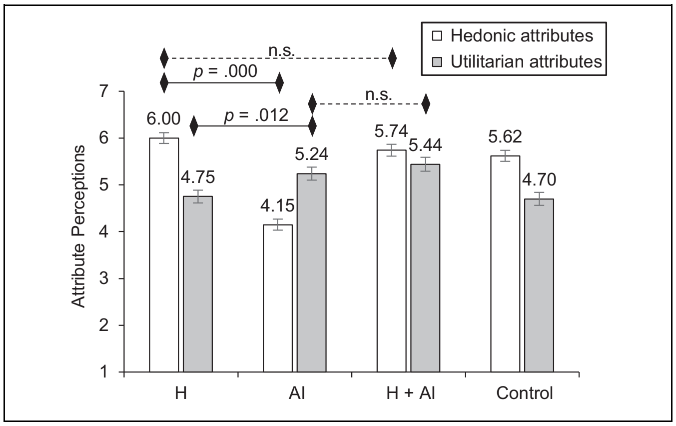

Figure 4. Results of Study 6: The word-of-machine effect is eliminated in the case of augmented intelligence (human–AI hybrid decision making).

Note. The y-axis represents hedonic attribute perceptions and utilitarian attribute perceptions measured on seven-point scales anchored at 1 = "very low," and 7 = "very high." Error bars represent standard errors. The solid-line pairwise comparisons represent the word-of-machine effect. The dashed-line pairwise comparisons represent moderation by augmented intelligence: A human–AI hybrid decision making model bolsters AI to the level of humans for hedonic decision making, and humans to the level of AI for utilitarian decision making. Details of all pairwise comparisons are reported subsequently.

Hedonic Attribute Perceptions
Word-of-machine effect: Human versus AI: $F(1, 436) = 125.55$, $p = .000$
Moderation by augmented intelligence (H + AI hybrid decision making bolsters AI to the level of humans for hedonic decision making): Human versus H + AI: $F(1, 436) = 2.31$, $p = .129$
AI versus H + AI: $F(1, 436) = 84.73$, $p = .000$
Control versus H: $F(1, 436) = 5.32$, $p = .022$
Control versus AI: $F(1, 436) = 77.92$, $p = .000$
Control versus H + AI: $F(1, 436) = .49$, $p = .486$

Utilitarian Attribute Perceptions
Word-of-machine effect: Human versus AI: $F(1, 436) = 6.40$, $p = .012$
Moderation by augmented intelligence (H + AI hybrid decision making bolsters H to the level of AI for utilitarian decision making): AI versus H + AI: $F(1, 436) = .99$, $p = .321$
H versus H + AI: $F(1, 436) = 11.87$, $p = .001$
Control versus H: $F(1, 436) = .05$, $p = .820$
Control versus AI: $F(1, 436) = 7.47$, $p = .007$
Control versus H + AI: $F(1, 436) = 13.22$, $p = .000$

Studies 7a–7b: Attenuating the Lay Belief Underlying the Word-of-Machine Effect

Studies 7a and 7b test an intervention to attenuate the lay belief underlying the word-of-machine effect—that AI recommenders are less (more) competent than human recommenders in assessing hedonic (utilitarian) value. We used a protocol called "consider-the-opposite," in which people are prompted to consider the opposite of what they initially believe to be true and take into account evidence that is inconsistent with one's initial beliefs. This protocol has been effectively used to correct biased beliefs in judgment, such as the explanation bias (Lord, Lepper, and Preston 1984), confirmatory hypothesis testing (Wason and Golding 1974), anchoring (Musselweiler, Strack, and Pfeiffer 2000) and halo effects in marketing claims (Ordabayeva and Chandon 2016). Study 7a tests this intervention following the original protocol (i.e., Musselweiler, Strack, and Pfeiffer 2000), and Study 7b tests a protocol that is relatively easier to implement and scale by embedding the intervention in a real chatbot.

Study 7a: Testing the Original Consider-the-Opposite Protocol

Procedure. Three hundred sixty-eight respondents ($M_{age} = 39.8$ years, $SD = 12.5$; 49.2% female) from Amazon Mechanical Turk participated in exchange for monetary compensation in a 2 (recommender: human, AI) × 2 (intervention: consider the opposite, control) between-subjects design.

The stimuli and procedure were identical to those of Studies 4 and 6: participants read about a new app created to give chocolate recommendations by relying on either a human or an AI master chocolatier. We manipulated recommender between subjects by telling participants that, in the version of the app they were considering, it was either the human or the AI chocolatier that would suggest a curated selection of five chocolate bars. We also implemented the intervention between subjects by prompting half of the participants to "consider the opposite": consider the ways in which they could be wrong about what they expected the [human/AI] recommender to be good at (based on Musselweiler, Strack, and Pfeiffer 2000):

> Think for a moment about what you expect the [human/AI] chocolatier to be good at when selecting chocolate bars. Before you rate the chocolate selection, we would like you to consider the opposite. Can your expectations about what the human chocolatier is good at when selecting chocolates be wrong? Imagine that you were trying to be as unbiased as possible in evaluating this chocolate selection—consider yourself to be in the same role as a judge or juror. Could the [human/AI] chocolatier be good at the opposite of what you expect them to be good at? Please write down some ways in which you could be wrong in terms of your expectations about what the [human/AI] chocolatier is good at when selecting chocolates.

This prompt was absent for participants in the control condition. As a dependent variable, participants reported their perceptions of hedonic/utilitarian attributes of the curated selection of chocolate bars, measured on a seven-point scale ranging from 1 = "sensory pleasure (taste, aromas, etc.)" to 7 = "healthy chemical properties (antioxidants, micro/macro nutrients, etc.)." Thus, lower numbers indicated higher hedonic value.

Results and discussion. A 2 × 2 ANOVA on hedonic/utilitarian attribute perceptions revealed no significant main effect of intervention ($F(1, 364) = .25$, $p = .62$), a significant main effect of recommender ($F(1, 364) = 65.17$, $p < .001$), and a significant two-way recommender × intervention interaction ($F(1, 364) = 12.11$, $p = .001$). Planned contrasts revealed that the word-of-machine effect replicated both in the control and intervention conditions, with lower hedonic perceptions (or, conversely, higher utilitarian perceptions) for AI recommenders than human recommenders (control conditions: $M_{AI\_control} = 4.51$, $SD = 1.84$, $M_{H\_control} = 2.49$, $SD = 1.48$; $F(1, 364) = 81.48$, $p < .001$; intervention conditions: $M_{AI\_intervention} = 3.99$,

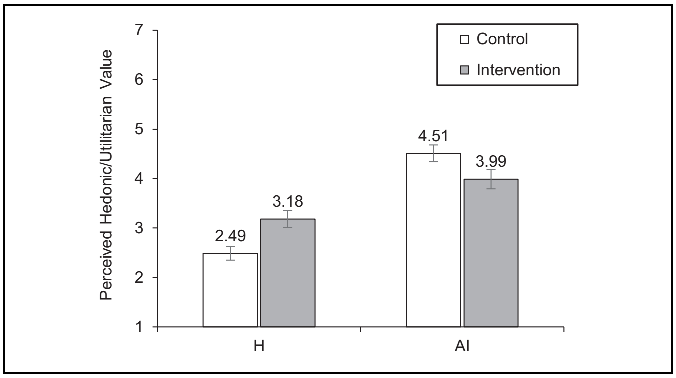

Figure 5. Results of Study 7a: Prompting people to consider the opposite attenuated the word-of-machine effect.

Notes. The y-axis represents perceived hedonic/utilitarian attribute value measured on a seven-point scale anchored at 1 = "sensory pleasure (taste, aromas, etc.), and 7 = "healthy chemical properties (antioxidants, micro/macro nutrients, etc.)"; therefore, higher numbers indicate higher utilitarian value/lower hedonic value. Error bars represent standard errors.

SD = 1.78, $M_{H\_intervention} = 3.18$, SD = 1.44; $F(1, 364) = 8.93$, $p = .003$; higher numbers indicate higher utilitarian/lower hedonic perceptions). More importantly, the intervention attenuated the word-of-machine effect and led to participants perceiving the AI's recommendation as having higher hedonic value compared with the control condition ($M_{AI\_intervention} = 3.99$, SD = 1.78, $M_{AI\_control} = 4.51$, SD = 1.84; $F(1, 364) = 7.66$, $p = .006$) and the human recommendation as having higher utilitarian value compared to the control condition ($M_{H\_intervention} = 3.18$, SD = 1.44; $M_{H\_control} = 2.49$, SD = 1.48, $F(1, 364) = 4.59$, $p = .033$; higher numbers indicate higher utilitarian/lower hedonic perceptions; Figure 5).

Thus, these results provide evidence for a potential intervention that alleviates initial beliefs about, and therefore resistance to, AI recommenders: prompting people to consider the opposite.

Study 7b: Testing a Consider-the-Opposite Intervention That Is Easier to Implement and Scale

Study 7b builds on the original consider-the-opposite protocol and the results of Study 7a to test an intervention better suited for implementation and scalability in a real-world setting. To do so, we created a real chatbot that participants could interact with and that delivered the intervention.

Procedure. Two hundred nighty-nine respondents ($M_{age} = 40.4$ years, SD = 12.6; 43.1% female) from Amazon Mechanical Turk participated in exchange for monetary compensation in a two-cell (intervention: consider the opposite, control) between-subjects design. Participants read about an app called "Cucina" that would rely on AI to give recipe recommendations. The app worked by giving users the chance to chat with the AI Chef and ask for recipe suggestions and recommendations. Participants further read that they could try out the AI Chef by chatting with it in a web browser window. We created a chatbot ad hoc for this experiment by embedding a JavaScript in the Qualtrics survey (Figure 6). The chatbot was programmed to first introduce itself: "Hello I am an A.I. Chef at Cucina! Thank you for trying out our app! What is your name?" Participants could then reply to the chatbot using a text box. We programmed the chatbot's next response to differ depending on the intervention condition:

> [Intervention: consider the opposite] "Hi [participant's name]! I am here to suggest a recipe for you to try! Some people might think that an Artificial Intelligence Chef is not competent to give food suggestions... but this is a misjudgment. For a moment, set aside your expectations about me. When it comes to making food suggestions, could you consider the idea that I could be good at things you do not expect me to be good at? Okay, let's chat about food. How can I help you?"
>
> [Intervention: control] "Hi [participant's name]! I am here to suggest a recipe for you to try! Okay, let's chat about food. How can I help you?"

As a dependent variable, we measured hedonic/utilitarian attribute perceptions of the recipes suggested by the AI chatbot, as measured on a seven-point scale ranging from 1 = "mostly based on sensory pleasure (taste, aromas, etc.)" to 7 = "mostly based on healthy chemical properties (antioxidants, micro/macro nutrients, etc.)."

Results and discussion. A one-way ANOVA on hedonic/utilitarian attribute perceptions revealed that the intervention attenuated the word-of-machine effect and led to higher hedonic perceptions compared to the control condition ($M_{intervention} = 3.75$, SD = 1.46, $M_{control} = 4.25$, SD = 1.37; $F(1, 297) = 9.15$, $p = .003$; lower numbers indicate higher hedonic perceptions). These results corroborate those of Study 7a and provide evidence for a practical and relatively easier-to-implement intervention for managers looking to attenuate the lay belief underlying the word-of-machine effect.

General Discussion

As companies in the private and public sectors assess how to harness the potential of AI-driven recommendations, the question of how trade-offs in decision making influence preference for AI recommenders is of great importance. We address this question across nine studies and show a word-of-machine effect: the phenomenon by which hedonic and utilitarian trade-offs determine preference for (or resistance to) AI-driven recommendations. Studies 1a–1b show that a utilitarian (hedonic) goal makes people more (less) likely to choose AI recommenders than human ones. Study 2 shows that AI (human) recommenders lead to higher perceptions of utilitarian (hedonic) attributes upon consumption. Study 3 shows that people prefer AI (human) recommenders when utilitarian (hedonic) attributes are more important. Study 4 shows that differing competence perceptions underlie the word-of-machine effect and rule out complexity. Studies 5 and 6 identify boundary conditions: Study 5 shows that the word-of-machine effect is reversed for utilitarian goals if the recommendation

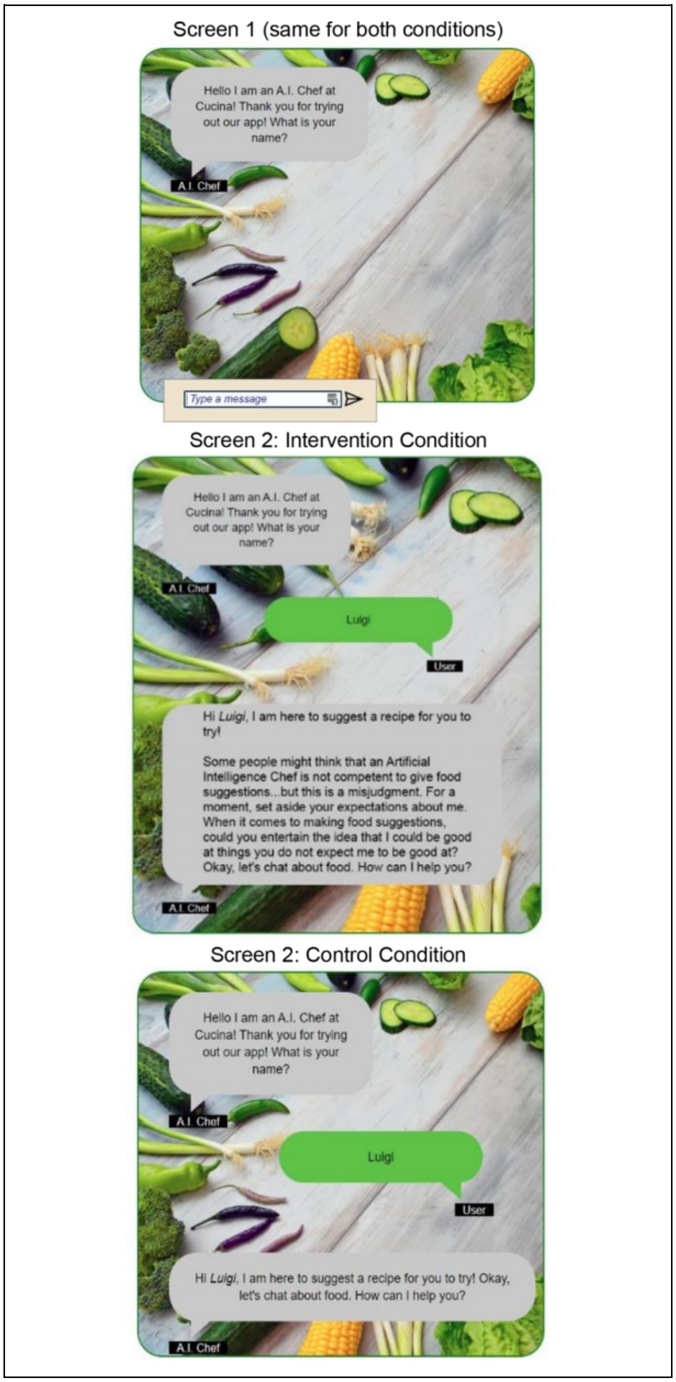

Figure 6. Stimuli of Study 7b.

needs to match a person's unique preferences, and Study 6 shows that the effect is eliminated when AI is framed as "augmented" rather than "artificial" intelligence, that is, in human–AI hybrid decision making. Finally, Studies 7a–7b tested an intervention to attenuate the word-of-machine effect.

Theoretical Contributions

Our research makes several important theoretical contributions. A first set of contributions speaks to research on the psychology of automation and on human–technology interactions (Dawes 1979; Groove and Meehl 1996; Meehl 1954). First, we extend this literature by addressing the question of whether hedonic/utilitarian trade-offs in decision making drive preference for or resistance to AI recommenders. This question is novel, as prior research has not relied on differences inherent to hedonic/utilitarian consumption to predict people's reactions to receiving advice from automated systems.

Second, we show under what circumstances AI-driven recommendations are preferred to, and therefore more effective, than human ones: when utilitarian attributes are relatively more important or salient than hedonic ones. Research in this area has largely focused on consumers' resistance to automated systems. For example, in the domain of performance forecasts, people are less likely to rely on the input of an algorithm than a person to make predictions about student performance, an effect that is due to the belief that algorithms, unlike people, cannot learn from their mistakes (Dietvorst, Simmons, and Massey 2014). In the domain of health care utilization, people are less likely to rely on an automated medical provider if a human provider is available, even when the two providers have the same accuracy (Longoni, Bonezzi, and Morewedge 2019, 2020).

Limited research has identified under what circumstances resistance to algorithmic advice is attenuated: if people have the opportunity to modify algorithms and thus exert control over them (Dietvorst, Simmons, and Massey 2016), if the human likeness of algorithms is increased (Castelo, Bos, and Lehman 2019), if the task entails a numeric estimate of a target (Logg, Minson, and Moore 2019), and if the algorithm is described as tailoring a recommendation to a person's unique case (Longoni, Bonezzi, and Morewedge 2019, 2020). We extend this literature by showing circumstances in which consumers' resistance to AI may be reversed and by showing cases in which consumers even prefer automated systems: when they assign greater importance to utilitarian attributes or when a utilitarian goal is activated.

Third, we explore under what circumstances consumers will be amenable to AI recommenders in the context of human–AI partnerships. We show that augmented intelligence helps bolster AI to the level of humans for hedonic decision making and helps bolster humans to the level of AI for utilitarian decision making. This contribution is important because it represents the first empirical test of augmented intelligence as an alternative conceptualization of artificial intelligence that focuses on AI's assistive role in advancing human capabilities. We hope that this contribution will prioritize new research focused on understanding the potential of AI in conjunction with humans rather than in contraposition, as this seems to be the advocated way forward by many practitioners (Araya 2019; Hao 2020).

We also contribute to the literature on hedonic and utilitarian consumption (Alba and Williams 2013; Khan and Dhar 2010; Moreau and Herd 2009; Whitley, Trudel, and Kurt 2018). Literature in this area has identified the factors that influence evaluation of hedonic and utilitarian product dimensions. We extend this literature by investigating how hedonic/utilitarian attribute trade-offs influence the effectiveness of a source of a product recommendation (i.e., a human vs. an AI recommender; Studies 1a, 1b, 3–5) and how the source of a product recommendation influences hedonic/utilitarian perceptions (Studies 2, 6–7b).

Managerial Implications

The current speed of development and adoption of AI, machine learning, and natural language processing algorithms challenge managers to harness these transformative technologies to optimize the customer experience. Our findings are insightful for managers as they navigate the remarkable technology-enabled opportunities that are growing in today's marketplace. These new technologies are also experiencing a renewed prominence in public discourse. For instance, the U.S. government has established the National Artificial Intelligence Research and Development Strategy to address economic and social implications of AI.

Our findings provide useful insights for both companies and public policy organizations debating if and how to effectively automate their recommendations systems. A company like Sephora relies both on human-based recommendations from sales associates and its customer base and AI-based recommendations through its Visual Artist app, a conversational bot that interacts with prospective shoppers. Our results suggest cases in which AI-based recommendations would be more effective (i.e., when utilitarian attributes are more salient or important, such as grooming products) and when they would be less effective (i.e., when hedonic attributes are more salient or important, such as fragrances).

Our results are insightful for strategic and tactical marketing decisions. Marketers could prioritize functional positioning strategies over experiential ones in the case of AI-based recommendations for target segments for whom utilitarian attributes are more important. For instance, a company in the hospitality industry such as TripAdvisor should emphasize AI-based recommendations for business travel services and deemphasize AI-based recommendations for leisure travel services. Our results also apply to a host of tactical decisions such as marketing communications. Managers could communicate to their customers in a way that is aligned with a target segment's goal (i.e., hedonic vs. utilitarian) and emphasize the most effective points of parity/difference with competing brands or across different products in the portfolio. Companies like Netflix and YouTube could emphasize AI-based recommendations when utilitarian attributes are relatively more important (e.g., documentaries) and human-based recommendations ("similar users") when hedonic attributes are relatively more important (e.g., horror movies).

This research also highlights boundary conditions that may prove useful for practitioners. Study 5 indicated that when consumers want recommendations that are matched to their unique preferences, they resist AI recommenders and instead prefer human recommenders, regardless of hedonic or utilitarian goals. These results suggest that companies whose customers are known to be satisfied with "one size fits all" recommendations, or who are not in need of a high level of customization, may rely on AI systems. However, companies whose customers are known to desire personalized recommendations should rely on humans. Some companies, such as Amazon, seem to be implementing a similar strategy. Even though most of Amazon's recommendations are based on algorithms, the company has recently started offering an additional service for an added fee called "personal shopper." This service relies on human shopping assistants to give clothing recommendations rather than on algorithms. Our results indicate that more companies, especially those in markets that are relatively more hedonic, should follow Amazon's example.

Study 6 provides another managerially relevant boundary condition: augmented intelligence. The results of this study indicate that consumers are more receptive to AI recommenders, even in the case of hedonic goals, if the AI recommender does not replace a human recommender but instead assists a human recommender who retains the role of ultimate decision maker. These results are important for practitioners managing relatively more hedonic products or services. For instance, in a personal conversation with the authors, a Walmart marketing manager noted how the top two most frequently ignored recommendations on the company's website are those for alcoholic beverages and food items—arguably products for which hedonic attributes tend to be more salient and important. In these circumstances, practitioners could leverage our results and utilize AI systems to generate an initial recommendation on which a human then "signs off."

Finally, in Studies 7a–7b we tested an intervention that practitioners managing relatively more hedonic products and relying on AI systems may execute. Building on the consider-the-opposite protocol, we created a realistic chatbot that interacted with participants and nudged them to consider that the AI recommender could be good at things that participants did not expect it to be good at. The intervention was successful in both studies, suggesting that practitioners may utilize this technique if hedonic attributes are important.

Limitations and Future Research

Despite the robustness of the word-of-machine effect, our research has limitations that offer several opportunities for future research. First, there is the possibility that drawing attention to the source of a recommendation primed study participants. AI recommenders might have primed utilitarian attributes or made utilitarian goals more salient, and it was the associated increased activation of these concepts, rather than competence perceptions, that gave rise to the word-of-machine effect. Although possible, this alternative explanation based on priming is unlikely given the results of a study we report in Web Appendix D. In this study (N = 230), we first primed participants with either human or AI-related concepts by drawing their attention to either a human or an AI recommender, thus approximating the kind of priming that could have occurred in our studies. To assess whether the AI recommender primed utilitarian concepts, we then measured perceptions of utilitarian and hedonic attributes of a stimulus in a domain unrelated to one in which the priming manipulation occurred. This stimulus was pretested to be neutral (i.e., perceived to be equally utilitarian and hedonic). The results indicate that the stimulus was perceived to be equally utilitarian and hedonic regardless of the priming manipulation. Although these results offer preliminary evidence that priming does not account for the word-of-machine effect, the inferences one can draw from a null effect are limited. More broadly, the question of whether AI-based recommendations activate specific constructs that might be influential on decision making is a worthy avenue for future research.

Second, even though we tested the word-of-machine effect across multiple domains, there remains the possibility that the effect is stronger or weaker in certain categories. For instance, the effect might be stronger in categories (e.g., a chocolate cake) in which discerning hedonic attributes (e.g., how tasty or how indulgent it is) is easier than discerning utilitarian attributes (e.g., how many macronutrients it contains, or how healthy it is). Future research could more systematically investigate what dimensions of different product categories strengthen versus weaken the word-of-machine effect.

Third, the lay beliefs underlying the word-of-machine effect may be transitional. As competence perceptions driving the word-of-machine effect are based on a lay belief, they are embedded in a cultural view that may change over time. The lay belief about differential competence perceptions may already be inaccurate, as AI is already utilized in domains that are relatively more hedonic. For instance, AI curates flower arrangements on the basis of customers' past transactions and inferred preferences (1-800-Flowers) and creates new flavors for food companies such as McCormick, Starbucks, and Coca-Cola (Venkatesan and Lecinski 2020).

Our research also suggests opportunities for future exploration of this area. First, the word-of-machine effect may have interesting downstream consequences on other responses. For instance, relying on an AI recommender may lead consumers to compensate by adjusting their own choices. Given the belief that AI-based recommendations excel on utilitarian attributes and are weaker on hedonic attributes, consumers may choose from a set of options by paying closer attention to the hedonic attributes of the options, assuming that the options are satisfactory in terms of utilitarian attributes. This "second-step choice" is an interesting question to consider in the future.

Second, in Studies 7a–b we show preliminary evidence of how lay beliefs toward AI systems could be successfully alleviated through a protocol utilized in the decision making literature. Future research could identify other real-world variables that might have similar attenuating effects, such as domain expertise, involvement, time spent making decisions, or familiarity/repeated use of AI systems. A third fruitful research opportunity would be to explore whether consumers can be persuaded to trust AI systems, even more than humans, in the eventuality that AI systems are sufficiently sophisticated to pass the Turing test. In this vein, future research could identify conditions under which the word-of-machine effect reverses, with AI recommenders being more persuasive than humans for hedonic products.

As research on the psychology of automation expands to include developments such as AI, we hope that our findings (especially those of Study 6) will spur further research prioritizing the understanding of the vast potential of AI operating in partnership with humans. More research is also necessary to map out the impact of AI systems across consumption settings. AI-powered technologies will be instrumental in optimizing the customer experience at each phase of the consumer journey by offering products of increasing personalization (Venkatesan and Lecinski 2020). New technologies like image, text, and voice recognition, together with large-scale A/B testing will provide managers with the data necessary for a complete, AI-driven customization of the journey (Venkatesan and Lecinski 2020) and will allow researchers to gather the consumer signals that are produced as a by-product of consumer activities (Schweidel et al. 2020). We hope that future research will focus on how to harness this great potential of AI for managers and researchers alike.

Overall, understanding when consumers will be amenable to and when they will resist AI-driven recommendations is a pressing and complex endeavor for researchers and firms alike. We hope that our research will spur further exploration of this important topic.

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