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Inferring one's own attitude toward an unknown attribute: The moderating role of complexity in juice tasting

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Abstract

This study examined how people learn about their own *summarized attribute preferences*: their overall evaluative summaries of an attribute (e.g., one's liking for “sweetness” or “crispness”). Participants tasted and evaluated 14 juices varying on (a) an unknown attribute “Barinium” (low-complexity condition), or (b) both Barinium and a second, unrelated attribute (high-complexity condition). Participants then reported their summarized preference for Barinium as the dependent variable. Results revealed that participants' *functional attribute preferences*—that is, the extent to which they actually liked the high versus low Barinium juices—predicted their summarized preference for Barinium. This functional-summarized preference association was stronger when the juices varied on Barinium alone rather than two attributes; that is, complexity caused participants to weigh their actual experiences of liking less when forming summarized preferences. Furthermore, functional and summarized preferences independently and simultaneously predicted participants' choice of juices to take home—especially when each juice sample was labeled with its Barinium content. Implications for attitudes and consumer research are discussed.

1 | INTRODUCTION

People can articulate their preferences for innumerable aspects of daily life. But how do people learn about their own preferences? A large body of research has examined how people form attitudes toward *objects* (i.e., nouns such as “fruit,” “Gala apples,” or famously “senior comprehensive exams;” Eagly & Chaiken, 1993; Petty & Cacioppo, 1984; Petty & Cacioppo, 2012; Petty et al., 1981). However, relatively little is known about how people form attitudes toward *attributes* (i.e., adjectives such as “sweetness,” “crispness,” or interpersonal qualities such as “ambitiousness;” Ledgerwood et al., 2018). There are reasons to suspect that the psychological process by which people learn how much they like an attribute could be even more intricate than the process by which they learn how much they like an object. After all, an attitude toward an attribute refers to a positive (or negative) evaluation of a *continuous dimension*, and so it likely entails a comparative process across multiple entities that possess high versus medium versus low levels of the attribute in question. Given the lack of research in this domain, the

goal of the current study is to explore how people generate a summary judgment of their liking for an unfamiliar attribute after they encounter varying levels of the attribute in a series of products (i.e., cranberry juices) for the first time.

Understanding attitudes is especially important in consumer contexts. Indeed, consumers' attitudes predict their purchasing intentions and behavior toward genetically modified foods (Bredahl, 2001), organic products (Lee & Yun, 2015; Samoggia & Riedel, 2018; Smith & Paladino, 2010), and luxury brands (Bian & Forsythe, 2012; Schade et al., 2016). Furthermore, consumers rely on these attitudes in real life when making choices in both (a) situations where product information is present (e.g., while shopping at a supermarket, Gidlöf et al., 2017) and (b) contexts where product information is absent (e.g., while “blind-tasting” wines, Lockshin & Corsi, 2012; Mueller & Szolnoki, 2010). Of course, the association between attitudes and behavior is far from perfect, and so it is important to document the contexts in which people's attitudes have stronger or weaker effects (Ajzen & Fishbein, 1977; Park & Lin, 2020). The current study advances a

novel approach to consumer behavior by examining how attitudes toward product *attributes* (rather than attitudes toward *objects*—or the products—themselves) predict behavioral consequences (i.e., product choice) in two real-world (i.e., labeled and unlabeled) contexts.

1.1 | Summarized and functional attribute preferences

Just as an attitude toward an object is a tendency to evaluate that object with a degree of favor or disfavor (Eagly & Chaiken, 1993), an attitude toward an attribute is a tendency to evaluate higher (versus lower) levels of a particular attribute with a degree of favor or disfavor. Importantly, attitudes toward attributes can be conceptualized in two distinct ways: *summarized attribute preferences* and *functional attribute preferences* (Ledgerwood et al., 2018). Summarized attribute preferences refer to an individual's summary judgment of an attribute as an overall concept, abstracted from any particular target object. For example, researchers assessing participants' summarized preference for sweetness in apples might administer the question "To what extent is the characteristic 'sweetness' in apples desirable to you?" on a scale from 1 (not at all) to 9 (very desirable).

Functional attribute preferences refer to the association between the level of an attribute in a set of targets and the extent to which an individual likes each target—that is, a functional preference is the extent to which a person actually experiences liking for the attribute (Ledgerwood et al., 2018, 2020). For instance, researchers assessing functional preferences for sweetness in a series of apples might calculate each participant's within-person association of apple sweetness with their liking for each apple. Given that attributes vary on a dimension (by definition), any attitude toward an attribute can be conceptualized and measured as a summarized preference and/or a functional preference.¹

1.2 | Summarized and functional attribute preferences in different research fields

Consumer research on food and drink occasionally assesses individuals' preferences for product attributes. In this literature, functional preferences are common: Researchers typically assess functional preferences by first assessing the extent to which various attributes are objectively present in each sample (as determined by panels of experts in sensory evaluation), and then calculating how strongly these attributes are associated with consumers' liking for each sample in taste tests. The goal of this procedure is to determine the "drivers of liking" of these foods (Lawless & Heymann, 2010). For example, Delgado and Guinard (2011) examined 22 samples of extra virgin olive

oil and found that positive drivers of consumers' liking included fruitiness, nuttiness, and buttery flavors. In similar studies, sweetness and smooth texture proved to be drivers of liking for sweet potatoes (Leksrisonpong et al., 2012), and firmness and sweetness were drivers of liking for apples (McCracken et al., 1994; Seppä et al., 2013). Summarized preferences are somewhat rare in this field (for one example with attributes of apples, see Seppä et al., 2013).

There are (perhaps surprising) parallels in research on human mating. Summarized preferences are a central construct in this literature: Studies from disciplines spanning sociology, personality psychology, evolutionary psychology, and close relationships have assessed participants' summarized preferences by asking them to rate the extent to which attributes such as "physically attractive," "intelligent," or "nurturing" are likeable or important in a romantic partner (Brumbaugh & Wood, 2013; Buss, 1989; Csajbók & Berkics, 2017; Eastwick & Finkel, 2008; Fletcher et al., 1999; Hill, 1945; Wood & Brumbaugh, 2009). Human mating researchers have also measured functional preferences, albeit less commonly than summarized preferences. For instance, in one set of studies (Brumbaugh & Wood, 2013; Wood & Brumbaugh, 2009), researchers computed participants' functional preferences as the within-person correlation of (a) the level of an attribute depicted in each of a set of faces (e.g., "confident") with (b) the participant's attraction ratings to each face (see also DeBruine et al., 2006; Eastwick et al., *in press*).

1.3 | The correspondence between summarized and functional attribute preferences

Lessons about attribute preferences from the field of human mating may shed light on consumer attitudes. It is perhaps intuitive that summarized preferences (i.e., what we say we like) should be strongly correlated with functional preferences (i.e., what our ratings across multiple instances *reveal* we like). However, the existing evidence—which primarily comes from studies of human mating—suggests that these two constructs are far from identical. For instance, studies in which participants evaluated photographs of potential romantic partners have revealed moderate functional-summarized correlations, ranging from $r = .10$ to $r = .30$ (Brumbaugh & Wood, 2013; DeBruine et al., 2006; Eastwick & Smith, 2018; Wood & Brumbaugh, 2009). In speed-dating contexts, functional and summarized preferences seem to be uncorrelated (average $r = .05$; Eastwick & Finkel, 2008).

We are aware of only one consumer study that examined both functional and summarized attribute preferences. Specifically, Seppä et al. (2013) reported that consumers' ratings of ideal apple attributes only moderately reflected the attributes they actually liked. For example, whereas "sweetness" was rated higher than "sourness" as an ideal attribute, the tasting ratings indicated that the sour varieties of apples tended to be especially well liked. It is important to note that Seppä et al. (2013) reported their observations at the level of the sample (i.e., the entire group of consumers) rather than on a participant-by-participant basis, as in the human mating studies. Nevertheless, these findings suggest that there is perhaps modest correspondence between functional and summarized preferences in the consumer preferences domain, too.

¹The summarized versus functional distinction does not apply to objects, given that objects are not dimensions (Ledgerwood et al., 2018). That is, the functional preference concept applies to attributes rather than objects because attributes contain a natural contrast (high vs. low levels) as part of the evaluated entity itself.

1.4 | Complexity: A potential moderator

Ledgerwood et al. (2018) noted that the magnitude of summarized-functional preference correlations in prior studies seemed to decrease with increasing stimuli *complexity*—a term that they used to refer to the number of dimensions on which stimuli vary. The strongest correlation ($r = .47$) emerged in an unpublished study evaluating preferences for sweetness in cereal, a relatively low-complexity set of stimuli (Eastwick, 2009, Study 2). However, the small sample size ($N = 46$) and the fact that participants only imagined tasting the cereals limit the generalizability of these findings.

Weaker correlations emerged in studies examining the association between participants' functional and summarized preferences for attributes in images of people, which might be considered a moderately complex set of stimuli (Brumbaugh & Wood, 2013; Eastwick & Smith, 2018; Wood & Brumbaugh, 2009). Crucially, the weakest correlations were evident when participants evaluated one another in-person, and in-person interactions tend to be especially rich and complex (Eastwick & Finkel, 2008). Extrapolating from these observations, Ledgerwood et al. (2018) posited that stimuli complexity may weaken the correspondence between summarized and functional attribute preferences. In other words, as the number of attributes to track increases (i.e., from the relative simplicity of breakfast cereals to the complexity of live humans), it may be more difficult for people to infer their summarized from their functional preferences.

Eastwick et al. (2019) conducted a series of experiments to examine how individuals translate their functional to summarized preferences and the impact of stimuli complexity on this process. In one of these experiments, the researchers used a dating-game paradigm to manipulate participants' functional preferences for a novel, fictional attribute (*Melb*: the ability to move objects with one's mind) across multiple targets ("dates"). In one condition, *Melb* was strongly associated with high likeability in the target dates, whereas in the other condition, it was only weakly associated with likeability. The researchers also manipulated stimuli complexity such that participants evaluated targets that varied on one (i.e., low complexity) or two (i.e., high complexity) continuous novel attributes. After playing the dating game, participants reported their summarized attribute preference for *Melb*. Consistent with the between-study analysis of Ledgerwood et al. (2018), the correspondence between participants' functional and summarized preferences was much stronger in the low than the high complexity condition. In summary, these findings indicate that individuals are able to infer their summarized from functional preferences for novel attributes, but this process may be easiest when evaluating unidimensional rather than multidimensional stimuli.

1.5 | Choices in attribute-blind versus attribute-labeled contexts

Presumably, summarized and functional preferences have meaningful consequences; that is, they should direct participants to choose targets that possess high rather than low levels of the

attribute. But it remains unclear whether summarized or functional preferences have a stronger ability to predict choice, and we know little about the circumstances that might cause one or the other to be more consequential.

One such circumstance might be the extent to which the attribute is clearly labeled (or not) in the set of possible choices. Indeed, marketing researchers are often interested in the way that labeling products influences consumer behavior: In marketing studies, consumers evaluate and choose from product samples labeled with information such as brand, variety (e.g., "Gala"), or facts related to farming practices or nutrition (Grunert et al., 2014; Lawless & Heymann, 2010). In many real-world purchasing settings, the consumer is unable to interact directly with the products (e.g., the cereal aisle at a grocery store), and so they must rely instead on information that can be acquired visually (Gidlöf et al., 2017). For instance, studies using eye-tracking techniques and actual grocery store sales data have found that the placement of products on the shelves and the relative salience of product signage influence purchasing behavior (Clement et al., 2015). In these contexts, purchasing choices presumably happen at the intersection of consumers' preexisting preferences and whatever labeled information manages to capture their visual attention.

In contrast, typical sensory evaluation tests are more like "blind-tasting" and deemphasize attribute-labeling (Delgado & Guinard, 2011; Leksrisompong et al., 2012; Seppä et al., 2013). In real-world purchasing contexts that mimic these studies (e.g., in tasting rooms, Lockshin & Corsi, 2012; Mueller & Szolnoki, 2010), consumers must rely primarily on their senses when evaluating products. For example, consumers typically use sensory cues (e.g., an apple's color) to make purchasing decisions in situations where product labeling is minimal (e.g., the produce display at a grocery store; Kleih & Sparke, 2021), and wine-tasting rooms often provide consumers an opportunity to focus on what they like and do not like in the glass, rather than relying on their ideas about what they like. In summary, both marketing studies and sensory evaluation tests provide essential insights with real-world consumer implications, but the way people draw from their existing preferences across the two contexts could be quite different.

Existing studies have examined how individuals' attitudes toward *objects* (e.g., products such as butter, yogurt, milk, coffee, soft drinks) predict their judgments about those objects in labeled and/or blind contexts (e.g., Aaron et al., 1994; Maison et al., 2004; Paasovaara et al., 2012; Shepherd et al., 1991; Sörqvist et al., 2013). However, researchers have yet to explore how *attribute* preferences affect product choice across these two contexts, nor have they examined the differential impact of functional versus summarized preferences on choice. There is (to our knowledge) one relevant article: da Silva Frost et al. (in press) found that summarized attribute preferences predicted participants' choices to join certain dating websites after reading about them, whereas functional attribute preferences predicted participants' choices after they had actual experience with the websites. Our study was also designed to examine whether summarized and functional preferences have distinct consequences for choice.

1.6 | Research aim of this study

Influenced by recent human mating and consumer research, the current study tests the hypothesis that complexity moderates the association between participants' functional and summarized preferences for an unknown attribute. However, in contrast to the study design used by Eastwick et al. (2019), the current design did not manipulate functional preferences for a novel *imaginary* attribute but instead allowed participants to experience their own functional preferences for an unfamiliar *real* attribute as they evaluated a set of stimuli. In the current research, participants tasted and rated a series of juice samples in the lab—while tracking one (or two) unfamiliar attribute(s)—and then reported their summarized preference for the attribute. Thus, the current study tests whether stimuli complexity hinders participants' ability to translate their actual, experienced functional attribute preferences into summarized preferences in an externally-valid setting.

To test the predictive power of functional and summarized preferences, we also examined participants' choices between different juice samples that were labeled (i.e., the level of the unfamiliar attribute was visibly attached to the sample) or that were unlabeled (i.e., the attribute had to be discerned from blind-tasting). Given (a) existing evidence that indirectly interacting with a product (e.g., reading its description) elicits abstract mental representations (Hamilton & Thompson, 2007), and (b) that summarized preferences for attributes are relatively abstract entities and seem to have greater predictive power in indirect settings (e.g., when rating online dating profiles; Brandner et al., 2020; da Silva Frost et al., *in press*; Eastwick et al., 2011; Huang et al., 2020), it seemed plausible that summarized preferences would have greater predictive power in the labeled versus the blind condition.

2 | METHODS

2.1 | Participants

Participants were $N = 485$ UC Davis undergraduates who earned Psychology course credit for completing this laboratory study. Of these individuals, five were granted immediate credit and dismissed after reporting relevant food allergies (e.g., cranberry, gluten). An additional three participants left before completing key components of the survey: two individuals left part way through tasting the study stimuli, and one did not complete the summarized preference measure. These eight participants were excluded from subsequent analyses, making our final sample size $N = 477$ undergraduate students (20.46% men, 78.49% women, 0.42% trans men, and 0.63% genderqueer; aged 18–34, $M_{\text{age}} = 19.81$, $SD = 1.96$). The racial/ethnic makeup of the participants was: 1.68% Black, African-American, and Caribbean American; 49.90% Asian-American, Asian, and Pacific Islander; 13.26% European-American, Anglo, and Caucasian; 25.68% Hispanic-American, Latinx, and Chicano/a; 0.21% Native American and American Indian; 6.95% Biracial or Multiracial, and 2.32% “Other”.

The recruitment and analysis plan was preregistered in February of 2019 and can be found [here](#) (along with data and code [here](#)). An earlier pilot study with $N = 143$ participants found that the functional-summarized association was $r = .54$ in the low complexity condition and $r = .29$ in the high complexity condition; the effect size difference between the two conditions is $q = .31$. We therefore decided to recruit at least $N = 450$ for the current study, which provides 90% power (at $\alpha = .05$) to detect $q = .31$.

2.2 | Procedure and materials

Each study session lasted approximately 30 min and was conducted by one member of a team of undergraduate research assistants. Assistants were trained by the second author according to a rigorous experimenter protocol and were completely blind to the study's hypotheses. The survey began with an informed consent form, followed by a checklist where participants indicated whether they were allergic to various ingredients (e.g., cranberry, food coloring, gluten, sucrose). If participants indicated having allergies to ingredients involved in the study, the research assistant told them that they could receive credit and exit the study immediately if they wished.

Participants then watched a short instructional video. The video began with a prompt informing participants that they would be sampling and evaluating a series of products during the study. Next, the video familiarized participants with the general layout of their place-mats, which contained 14 samples of juice, 14 samples of water, and 14 oyster crackers (Figure 1). The video noted that after all juices were sampled, participants would answer additional questions regarding their experience.

2.2.1 | Manipulating stimuli complexity

Participants in the low complexity condition ($N = 252$; Figure 1, Panel A) learned that they would be sampling 14 juices (i.e., samples A–N) that contained varying amounts of Barinium, an unfamiliar substance supposedly created in the lab and “derived from natural organic compounds” (in reality, Barinium was sugar). There were seven levels of Barinium (varying from “0” to “6 ml”) across the 14 juices; each level appeared twice. Participants in the high complexity condition ($N = 225$; Figure 1, Panel B) learned that they would be sampling 14 juices that contained varying amounts of Barinium and Willumite, another unfamiliar substance supposedly created in the lab (in reality, Willumite was tasteless food coloring ranging from bright pink to dark blue). Willumite also had seven levels (varying from “0” to “6 ml”) across the 14 juices, and each level appeared twice. Barinium and Willumite levels for each sample were chosen so that they were uncorrelated ($r = .02$ across the 14 juices); see Table 1 for the exact sample specifications. The instructional video emphasized that participants should pay attention to all aspects of the juices and “...how much you like or dislike each sample, as well as the amount of Barinium (or Barinium and Willumite) in each one.”

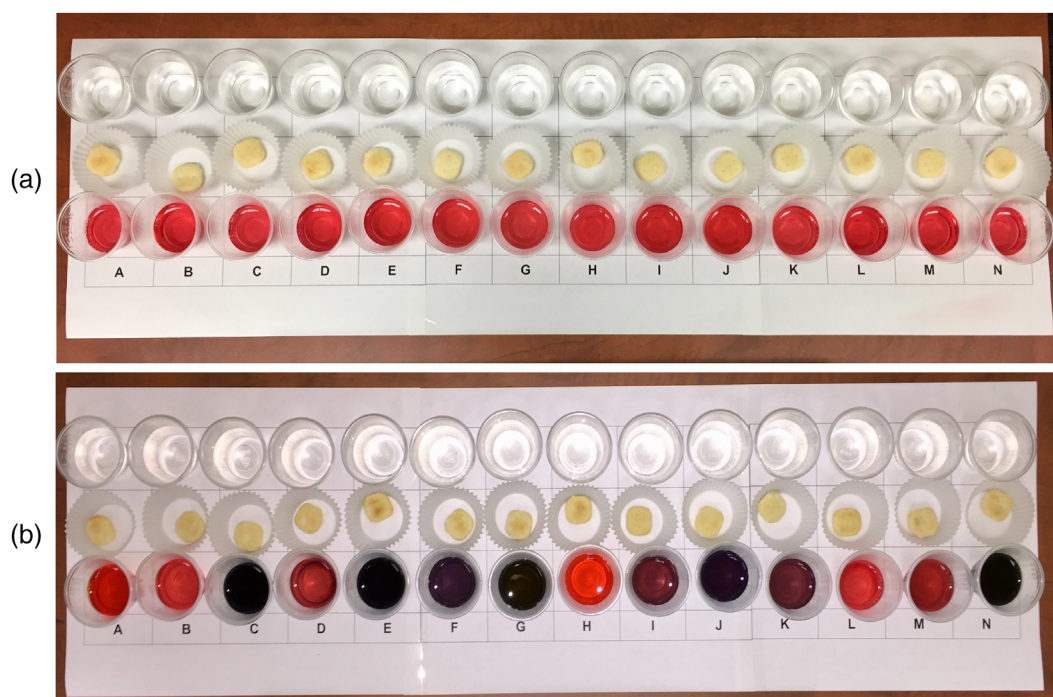


FIGURE 1 Juice tasting presentation. (a) depicts the low complexity (Barinium only) condition; (b) the high complexity (Barinium and Willumite) condition. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/ch.2082)]

2.2.2 | Juice tasting

The survey prompted participants to drink and evaluate each of the 14 cups of juices (in an order randomly generated by the survey). For each juice, participants drank the juice, rated the juice on a scale from 1 (*dislike extremely*) to 9 (*like extremely*), and then ate one cracker and drank one sample of water (to cleanse their palate). Each rating-scale page listed the amount (i.e., an integer between 0 and 6 ml) of Barinium (in the low complexity condition) or the amount of Barinium and Willumite (in the high complexity condition) contained in the specific juice. In total, the timed task took participants approximately 13 min to complete.

2.2.3 | Barinium collection choice task

Next, participants learned that they would have an opportunity to choose between two “collections” of (low complexity) juices to take home. One of these collections was lower in Barinium than the other collection, on average; Barinium level was counterbalanced across (a) the collection names (i.e., the “Heritage Collection” and the “Vintage Collection”), and (b) across the left versus right position in the presentation. The four juices in the low Barinium collection had Barinium levels equivalent to the 1, 2, 3, and 4 ml samples in Table 1, and the four juices in the high Barinium collection had levels equivalent to 3, 4, 5, and 6 ml samples. Levels of Barinium content overlapped between juice collections to

better approximate realistic tasting experiences, as real products vary on many dimensions and are therefore likely to have some overlapping attributes.

Some participants were randomly assigned to an attribute-labeled condition ($N = 237$) in which they viewed images of the two collections side-by-side; all eight juices appeared on their computer screen along with their Barinium levels. The instructions told participants to “read about and consider each juice collection you see on the screen” and then choose one to take home. The remaining participants in the attribute-blind condition ($N = 238$) were presented with actual trays containing the two collections side-by-side. These trays looked identical to the on-screen presentation in the attribute-labeled condition, except there were no labels indicating the levels of Barinium in each juice. The instructions told participants to “taste and consider each juice collection you see in front of you” and then choose one to take home.

At the very end of the study, participants provided free responses to the *Barinium description* item: “Please describe what the ingredient Barinium was like to you.” (See Supporting Information, Data S1, for coding of participants' responses.) They then learned that Barinium and Willumite referred to sweetness and color, which were renamed to minimize the influence of participants' pre-existing attitudes toward certain ingredients. Participants also received (if they wished) several juice boxes to take home that (approximately) corresponded to the Barinium collection they selected. Finally, participants were granted credit in SONA.

TABLE 1 Juice stimuli and ingredients

Sample name	A	B	C	D	E	F	G	H	I	J	K	L	M	N
<i>Purported ingredients</i>														
“Barinium (ml)” (both complexity conditions)	3	5	2	0	1	4	6	5	1	2	6	0	4	3
“Willumite (ml)” (high complexity only)	0	1	5	2	5	4	6	0	3	4	3	1	2	6
<i>Actual ingredients</i>														
Cranberry (oz)	.25	.25	.25	.25	.25	.25	.25	.25	.25	.25	.25	.25	.25	.25
Water (oz)	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Simple Syrup (oz)	1.5	2.5	1	0	0.5	2	3	2.5	.5	1	3	0	2	1.5
Yellow (drops)	30	0	0	0	0	0	6	30	0	0	0	0	0	6
Red (drops)	0	0	1	0	1	0	0	0	0	0	0	0	0	0
Blue (drops)	0	0	10	1	10	6	4	0	3	6	3	0	1	4
Green (drops)	0	0	3	0	3	0	6	0	0	0	0	0	0	6
<i>Average liking for sample</i>														
Low complexity condition	6.8 (1.3)	6.8 (1.7)	5.5 (1.7)	2.2 (1.4)	3.8 (1.7)	6.9 (1.6)	6.6 (2.1)	6.7 (1.9)	3.9 (1.7)	5.4 (1.7)	6.6 (2.0)	2.2 (1.3)	6.9 (1.6)	6.6 (1.5)
High complexity condition	6.4 (1.6)	7.1 (1.8)	5.2 (1.6)	2.3 (1.4)	3.4 (1.6)	6.9 (1.5)	7.0 (1.9)	7.0 (1.6)	3.8 (1.6)	5.3 (1.6)	7.1 (1.8)	2.2 (1.4)	7.2 (1.3)	6.4 (1.6)

Notes: Ingredients within a column were used to create one “batch” of juice, which was then used to fill the samples. Barinium levels 0–6 reflect increasing levels of simple syrup (i.e., sugar). Willumite levels 0–6 reflect increasing “cool blue” coloring. Participants rated their liking for each sample on a 1–9 scale; SDs in parentheses following each mean.

3 | MEASURES

3.1 | Functional preferences for Barinium

Each participant's functional preference for Barinium was their personal within-person association (i.e., regression beta) between the level of Barinium (i.e., 0–6) in each juice sample and their liking rating (i.e., on the 1–9 scale) of each juice across the 14 samples. We Fisher-z transformed these values for analyses reported below. We preregistered that participants would be excluded from analyses if they provided the same liking ratings to all 14 juices, but no participant did so.

3.2 | Summarized preferences for Barinium

Upon completion of the juice-tasting task, participants answered several questions about their attitudes and experiences, including the following four questions on a 1 (*not at all*) to 9 (*extremely*) scale: “How important is Barinium to you in a beverage?”, “How much do you value Barinium in a beverage?”, “How desirable is Barinium to you in a beverage?”, and “To what extent does Barinium characterize your ideal beverage?” (adapted from Eastwick et al., 2019). Each participant's summarized preference was the average of these four items ($\alpha = .92$). Participants in the high complexity condition also completed these same items about Willumite ($\alpha = .90$).

4 | RESULTS

4.1 | Descriptive statistics

Means and *SDs* for functional and summarized preferences are presented separately by complexity condition in Table 2. We did not have any a priori predictions about whether complexity would exert a main effect on functional preferences or on summarized preferences. Participants had slightly higher functional preferences for Barinium in the high than low complexity condition, $t(475) = -2.85, p = .005$. Summarized preferences for Barinium did not differ between the high and low complexity condition, $t(475) = 0.26, p = .794$.

We also did not have any a priori predictions about participants' functional or summarized preferences for Willumite (which was only relevant to the high complexity condition). Participants exhibited only a weak functional preference for the “cool blue” coloring of Willumite ($M = 0.04, SD = .17$); indeed, this value was not appreciably different from zero in a one-sample *t*-test, $t(224) = 1.83, p = .068$. Participants also reported a neutral summarized preference for Willumite ($M = 3.37, SD = 1.57$), and the summarized-functional correlation for Willumite was $r = .21, p = .001$.

4.2 | Functional-summarized correspondence

To assess whether the complexity of the juice stimuli moderated the magnitude of the functional-summarized preference correlation, we first

calculated the association of participants' Fisher-transformed functional preference for Barinium with their summarized preference, separately by complexity condition. In the low complexity condition, the functional-summarized Pearson correlation was $r = .54 (N = 252, p < .001)$, and in the high complexity condition, the Pearson correlation was $r = .35 (N = 225, p < .001; Figure 2)$. Descriptively speaking, participants' summarized preferences were more likely to track their functional preferences when juices varied on one trait (i.e., low complexity) rather than two (i.e., high complexity). The regression slopes were approximately linear in that the addition of the quadratic term for functional preferences did not significantly predict summarized preferences over and above the linear term for functional preferences, $ps > .218$.

Next, we compared the two functional-summarized preference associations ($r = .54$ vs. $r = .35$) using three different approaches. We preregistered all three and decided a priori that we would focus on the pattern of *p*-values and effect sizes across all three tests.

First, we conducted a *z*-test of the difference between the two functional-summarized preference correlations using an online calculator (Preacher, 2002). The difference between Pearson correlations was statistically significant ($z = 2.59, p = .010$), indicating that the correlation between functional and summarized preferences for Barinium was significantly stronger in the low complexity than high complexity condition.

Second, we examined whether complexity condition interacted with participants' functional preferences to predict summarized preferences. In a regression model predicting summarized preferences from complexity (coded 1 = low, 2 = high), (Fisher-transformed) functional preferences, and the complexity \times functional preference interaction, the interaction was not significant: $\beta = -.17, t(473) = -1.07, p = .285$. In other words, according to this model, the effect of participants' functional preferences on summarized preferences did not depend on stimuli complexity.

Third, we tested the three-way interaction between complexity condition, summarized preference, and Barinium level predicting liking for each juice in a multi-level dataset with 14 rows per participant (i.e., one row per juice). The results of this regression equation (with juice nested within participant) are depicted in Table 3. Critically, the three-way interaction was significant, $\beta_7 = -.11, t(476.30) = -3.38, p = .001$. In other words, complexity significantly moderated the correspondence between the summarized preference and the Barinium-liking effect (i.e., the functional preference).

In short, two out of three tests supported our prediction that the association of functional with summarized preferences would be significantly stronger in the low complexity compared to the high complexity condition, and the effect size in the nonsignificant test was nevertheless moderately sized in the correct (negative) direction. Thus, we tentatively conclude that stimuli complexity moderated the association of participants' functional with summarized preferences for Barinium.

4.3 | Functional preferences and summarized preferences predicting collection choice

At the end of the study, participants chose to take home either a low Barinium (coded = 0) or high Barinium (coded = 1) collection of juices

TABLE 2 Descriptive statistics for Barinium preferences

	Functional preference for Barinium							Summarized preference for Barinium						
	Mean	SD	N	Min	Max	Skew	Kurt.	Mean	SD	N	Min	Max	Skew	Kurt.
Low complexity	0.94	0.62	252	-1.34	2.09	-0.91	0.93	6.04	1.83	252	1.00	9.00	-1.04	0.47
High complexity	1.09	0.50	225	-0.93	2.00	-1.01	1.50	5.99	1.83	225	1.00	9.00	-0.95	0.39
Overall	1.01	0.57	477	-1.34	2.09	-1.01	1.33	6.01	1.83	477	1.00	9.00	-0.99	0.41

Notes: Functional preference values are within-person regression betas that predict each participant's liking (on a 1–9 scale) for each of the 14 juices from its Barinium content (0–6 scale); these values were then Fisher-transformed.

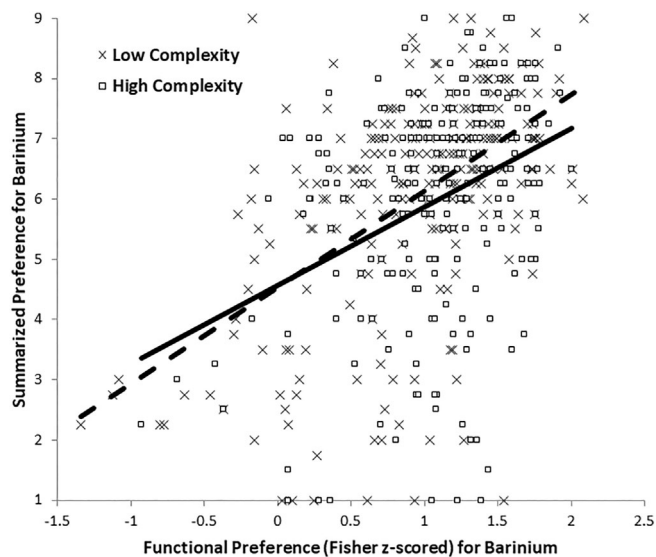


FIGURE 2 Scatterplot of functional preferences predicting summarized preferences. Dashed line is the trendline for the low complexity condition; bolded line is the trendline for the high complexity condition.

in either an attribute-labeled or attribute-blind condition. We preregistered and conducted three different tests of the predictive effects of functional and summarized preferences on choice. First, we conducted logistic regressions predicting collection choice, separately for functional and summarized preferences and separately for the attribute-labeled and attribute-unlabeled conditions (i.e., four total regressions). Second, we conducted logistic regressions predicting collection choice from both functional and summarized preferences simultaneously, separately for the attribute-labeled and attribute-blind conditions (i.e., two total regressions). Third, we conducted a structural equation model predicting collection choice from both functional preferences (a single measured variable) and summarized preferences (a latent construct with four indicators) simultaneously, separately for the attribute-labeled and attribute-blind conditions (i.e., two sets of SEM path estimates).

The results of these models are depicted in Table 4. All associations of summarized and functional preferences with the choice of the high (vs. low) Barinium collection were significant. Generally speaking, the functional preference associations tended to be stronger than the summarized preference associations, and effect sizes were smaller in

TABLE 3 Multilevel regression testing complexity moderation

Parameter	Estimate	t/z
<i>Fixed effects</i>		
Intercept (β_0)	5.49	157.93***
Complexity (β_1)	0.02	0.51
Barinium (β_2)	1.55	46.86***
Summarized Preference (β_3)	0.13	3.76***
Complexity \times Barinium (β_4)	0.10	3.00**
Complexity \times Summarized Preference (β_5)	0.01	0.22
Barinium \times Summarized Preference (β_6)	0.39	11.87***
Complexity \times Barinium \times Summarized Preference (β_7)	-0.11	-3.38**
<i>Random effects</i>		
Intercept	0.41	10.97***
Barinium	0.36	10.49***
Intercept/Barinium covariance	0.11	4.31***

Notes: DV = liking for each of the 14 juices (on a 1–9 rating scale). Juice was nested within participant with unstructured random effects for the intercept (β_0) and for Barinium (β_2). The regression equation is: Juice Liking = $\beta_0 + \beta_1$ Complexity + β_2 Barinium + β_3 Summarized Preference + β_4 Complexity \times Barinium + β_5 Complexity \times Summarized Preference + β_6 Barinium \times Summarized Preference + β_7 Complexity \times Barinium \times Summarized Preference + error, where β_2 reflects the average functional preference (i.e., the association of the Barinium level of a given juice with liking for the juice), β_6 reflects the average association of summarized with functional preferences (i.e., whether functional preferences shift depending on summarized preferences), and β_7 tests whether the summarized-functional association varies depending on complexity condition. All predictors were standardized except for the DV juice liking, which remained on the original 1–9 scale. Column “t/z” contains t values for fixed effects and z values for random effects. * $p < .05$, ** $p < .01$, *** $p < .001$.

SEM than logistic regression. Intriguingly, in both the simultaneous regressions and the SEMs, both functional and summarized preferences predicted choice; in other words, people's ideas about their preferences (i.e., summarized preferences) predicted choice controlling for their experienced preferences (i.e., functional preferences), and vice versa. Finally, choice condition significantly moderated the effect of functional preferences using all three approaches: Functional preferences predicted choice more strongly in the attribute-labeled than the attribute-blind condition, a difference we did not anticipate. Summarized preferences tended to predict choice more strongly in

TABLE 4 Functional and summarized preferences for Barinium predicting high-Barinium collection choice

	Preference type	Attribute-labeled			Attribute-blind			Labeled vs. blind difference (<i>p</i> value)
		β	Critical ratio (B/SE)	Odds ratio (e^{β})	β	Critical ratio (B/SE)	Odds ratio (e^{β})	
Separate Logistic Regressions	Functional	1.631	7.17***	5.11	0.836	5.04***	2.31	.005
	Summarized	0.904	5.46***	2.47	0.617	4.22***	1.85	.195
Simultaneous Logistic Regressions	Functional	1.468	6.30***	4.34	0.687	3.80***	1.99	.008
	Summarized	0.525	2.73**	1.69	0.339	2.03*	1.40	.464
Structural Equation Models	Functional	0.482	8.01***	1.62	0.286	4.10***	1.33	.007
	Summarized	0.178	2.84**	1.19	0.163	2.23*	1.18	.708

Notes: β s are standardized estimates. Attribute-labeled versus attribute-blind difference tests were conducted as (a) the choice condition \times (functional or summarized) preference interaction for the logistic regressions, and (b) a 1 *df* test for the effect of setting the (functional or summarized) preference to be equal across choice condition in the structural equation model. * $p < .05$, ** $p < .01$, *** $p < .001$.

the labeled than blind conditions, too, but these differences were not significant (see Supporting Information, Data S1).

5 | DISCUSSION

5.1 | Primary findings

Participants tended to infer their summarized preferences from their functional preferences for Barinium, with functional-summarized correlations of $r = .54$ in the low complexity condition and $r = .35$ in the high complexity condition. Furthermore, participants seemed to be inferring their summarized from their functional preferences for Barinium to a greater extent when evaluating juices that varied on one rather than two continuous attributes, as two out of three preregistered approaches for statistically comparing these correlations across conditions were significant. This experimental evidence illuminates discrepant findings in the literature, potentially explaining why some studies (i.e., in moderate-complexity contexts, like when participants rate photographs) find modest functional-summarized correspondence and other studies (i.e., in high-complexity contexts, like when participants rate partners face-to-face) do not (Ledgerwood et al., 2018).

This finding is consistent with prior covariation research showing that tracking a greater volume of information increases memory load demands, thus making the judgment process more difficult (Arkes & Harkness, 1983; Pechmann & Ratneshwar, 1992; Shaklee & Mims, 1982). Likewise, consumer studies have found that adding unfamiliar attributes to product descriptions decreases consumers' evaluations of high complexity (but not low complexity) products, potentially due to the high perceived "learning cost" (i.e., the amount of cognitive effort needed to learn the attributes) in high-complexity contexts (Mukherjee & Hoyer, 2001). Similarly, it is plausible that participants in the current study were able to track how much they liked the high versus low Barinium juices more effectively in the condition requiring less cognitive effort. Thus, the functional-summarized correlation was strongest in the low complexity condition.

5.2 | Predicting collection choice

Both functional and summarized preferences for Barinium predicted participants' choices to take home juice samples containing high or low levels of the attribute. These results suggest that both (a) direct experiences with an attribute and (b) abstracted beliefs about the attribute may jointly influence choice behavior, reinforcing the value in assessing both constructs in a consumer context.

Descriptively speaking, functional and summarized preferences for Barinium had stronger predictive effects in the attribute-labeled than the attribute-blind condition—functional preferences significantly so. This finding suggests that it may generally be easier to predict individual differences in consumers' choices for familiar, labeled products than unfamiliar, unlabeled products. Consistent with this suggestion, one study examining consumer perceptions of fermented dairy products found a stronger association between hedonic ratings (e.g., ratings of pleasantness) and actual purchasing behavior in the branded than the blind-tasting condition (Kytö et al., 2018). In other words, the researchers were able to more precisely predict actual purchasing behavior when participants evaluated samples that included (vs. excluded) brand information. We found the same pattern: Clear Barinium labels (vs. taste buds alone) seemed to aid participants in relying on their own functional and summarized attribute preferences when making a choice.

This pattern suggests an intriguing discrepancy across different research paradigms that examine consumer behavior: It is possible that individual differences in consumer preferences will be easier to predict in marketing research settings (i.e., where product information is often present) compared to sensory evaluation settings (i.e., where products are unlabeled). Indeed, whereas marketing research focuses on individual differences between consumers (e.g., who does and does not respond to a particular brand label), sensory evaluation tests may aim to neutralize individual differences by screening panelists for sensory acuity and their level of familiarity with the testing procedures (Lawless & Heymann, 2010). The current study (and the work of Kytö et al., 2018) suggest that this disciplinary distinction may be rooted in

part in the simple task difference between evaluating a labeled versus an unlabeled product: Personal preferences may have stronger effects on the former than the latter.

One other study has examined the influence of summarized and functional preferences on choice simultaneously (da Silva Frost et al., *in press*). In these studies, summarized and functional preferences for both familiar attributes (e.g., intelligence, confidence) and unfamiliar attributes (a facial feature called Reditry) predicted participants' choices to join a dating website featuring potential partners with high versus low levels of the attribute. Intriguingly, participants' functional preferences were a stronger predictor of choice than summarized preferences when the participants sampled the website (as we found here), whereas the reverse pattern emerged when participants read a description of the website. It is not immediately obvious how our attribute-labeled and attribute-blind conditions map onto da Silva Frost et al.'s (*in press*) website-sampling versus website-description distinction. Our attribute-labeled condition featured individually labeled juices and perhaps tapped into participants' functional preferences more strongly than the brief, abstract website description in da Silva Frost et al. (*in press*).

5.3 | Strengths and limitations

The current study has several strengths. It is the first study to *measure* rather than *manipulate* participants' functional attribute preferences in a design that tests whether stimuli complexity moderates the association between functional and summarized preferences. Also, participants tasted the juices in person rather than evaluating hypothetical stimuli, and they made real choices at the end of the study. All these features enhanced the external validity of the study. Furthermore, by ensuring that the second ingredient Willumite involved a different sensory modality (specifically, vision rather than taste), we ensured that the juices tasted exactly the same across complexity conditions.

The current study also has numerous limitations. Our qualitative coding of participants' impressions of Barinium revealed that it may have been unnecessary to use a fictional name for the attribute (see Supplemental Materials), as the majority of participants intuited that they were evaluating sugar. However, as in the Reditry studies in da Silva Frost et al. (*in press*), we implemented this unfamiliar term for sweetness so that participants would treat the experience like a learning context; otherwise, participants would likely have simply reported their pre-existing summarized preference for sweetness. Had we used a difficult-to-identify flavoring that would be novel for most participants (e.g., Echinacea, boxwood), it is unknown whether these results would generalize. Furthermore, future studies should evaluate a greater number of attributes to better determine the extent to which complexity affects how people evaluate real-world stimuli. Finally, the study aimed to illustrate a domain-general inferential process, and our findings may not extend to some domain-specific processes; consumers' preferences for juices will differ from their preferences for mates in many ways.

6 | CONCLUSIONS

People have direct experiences of liking for attributes (i.e., functional preferences), and they have ideas about the attributes they like (i.e., summarized preferences). But the process by which people translate from one to the other remains unclear. Inspired by discrepant findings in the literature, we found that stimuli complexity moderated this process. Furthermore, both functional and summarized preferences predicted meaningful choice behavior in externally-valid contexts, highlighting the importance of these constructs to the field of consumer research. Participants' preferences were stronger in the attribute-labeled condition (compared to the attribute-blind condition), indicating that the presence of product information may facilitate researchers' abilities to predict individual differences in consumer preferences. This difference in predictive power may parallel a key difference between marketing studies and sensory evaluation tests: Marketing designs may actually elicit individual differences more than sensory evaluation tests do. The current study thus integrates theory and research on attitudes, human mating, and consumer behavior, and thereby bolsters our understanding of the process by which people figure out what they like—and why it matters.

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CONFLICT OF INTEREST

The authors have no conflicts of interest to report.

DATA AVAILABILITY STATEMENT

The data and code that support the findings of this study are available in The Open Science Framework here (along with the preregistered recruitment and analysis plan here).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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