Summarized Attribute Preferences Have Unique Antecedents and Consequences

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Abstract

People have ideas about the attributes (i.e., traits or characteristics that vary along a dimension) that they like in others (e.g., "I like intelligence in a romantic partner"), and these ideas about liking are called *summarized attribute preferences* (Ledgerwood et al., 2018). But where do summarized preferences come from, and what do they predict? Across four studies, we examined how people form summarized attribute preferences and whether they predict situation selection. We showed participants a series of photographs of faces and assessed both their experienced liking for an attribute (or *functional attribute preference*) as well as their inference about how much they liked the attribute in the abstract (their summarized attribute preference). Our results suggest that summarized attribute preferences—despite being (weakly) grounded in functional attribute preferences—were affected by incidental aspects of the context in which people learn about them (i.e., the overall likeability of the pool of faces). Furthermore, we observed a double dissociation in the predictive validity of summarized and functional attribute preferences: Whereas summarized attribute preferences predicted situation selection at a distance (e.g., whether to join a new dating website based on a description of it), functional attribute preferences predicted situation selection with sampling (e.g., whether to join a new dating website after sampling it). We discuss theoretical and methodological implications for the interdisciplinary science of human evaluation.

Keywords: stated preferences, abstraction, covariation detection, situation selection, attraction

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Preferences for attributes are central to the way that people think about and experience the world. A person might profess their love of spiciness in food or their appreciation for intelligence in a romantic partner; someone might be drawn to an area of the country where residents are more liberal or more conservative; the brightness of an apartment might drive a person's interest in signing a lease. Perhaps unsurprisingly, multiple literatures have studied such preferences for *attributes*—that is, qualities that vary along a continuum (Anderson, 1971; Borgia, 1995; Buss, 1989; Eastwick et al., 2014; Fishbein & Ajzen, 1975; Lawless & Heymann, 2010).

Notably, these interdisciplinary literatures contain two very different ways of conceptualizing and measuring attribute preferences (Ledgerwood et al., 2018). One common approach to understanding attribute preferences has focused on how strongly a given attribute is associated with liking. This association is called a *functional attribute preference,* and it is characterized as a (within-person) valenced response to increasing levels of an attribute in a series of targets (e.g., the extent to which intelligence in a series of romantic partners predicts a person's liking for each partner; Wood & Brumbaugh, 2009). Functional preferences are the primary target of investigation by researchers who study attribute preferences in nonhuman animals (e.g., birds; Borgia, 1995; Moller, 1988; Patricelli et al., 2002); for example, researchers interested in understanding mate preferences in satin bowerbirds assess female birds' functional preference for vocal mimicry ability in a mate by measuring the strength of the association between (a) the accuracy and size of male birds' vocal mimicry repertoires and (b) the males' courtship success (Coleman et al., 2007). Some human literatures emphasize functional preferences, too (e.g., consumer preferences; Delgado & Guinard, 2011; Lawless & Heymann, 2010; organizational preferences; Heilman & Saruwatari, 1979; Turban & Keon, 1993).

Importantly, because humans can also abstract and articulate their likes and dislikes, a second approach to understanding attribute preferences is popular when studying humans (Anderson, 1968; Buss, 1989; Fletcher et al., 1999). This approach focuses on people's overall, summary evaluations of a given attribute in the abstract: A *summarized attribute preference* is a valenced response to an attribute as a concept (e.g., "I like intelligence in a romantic partner" or a negative gut reaction to the idea of ambitiousness in a leader). Summarized preferences are the primary target of investigation by researchers who study human mate preferences (e.g., Buss, 1989; Christensen, 1947; Fletcher et al., 1999, 2000; Hill, 1945), as well as preferences for attributes of friends and family members (Apostolou, 2007; Goodwin & Tang, 1991; see also Huang et al., 2020). For example, researchers in the fields of family studies, close relationships, and evolutionary psychology assess people's preferences for various attributes in a romantic partner by asking participants to rate how much they like or desire each attribute on a rating scale (e.g., a participant might rate the desirability of *attractiveness* or *intelligence* in a mate as a "7" on a 9-point scale ranging from 1 = *not at all desirable* to 9 = *extremely desirable*).

Because functional preferences and summarized preferences are largely studied in separate research traditions, much remains unknown about how they relate. Researchers assessing summarized preferences often seem to use them as proxies for functional preferences (e.g., Gerlach et al., 2019), and it seems plausible that people's ideas about their likes and dislikes draw from their experienced evaluations in the moment, at least to some extent (Ledgerwood et al., 2018). However, because summarized preferences reflect abstract, summarized ideas about liking—perhaps a uniquely human evaluative phenomenon—they may have antecedents and consequences that are distinct from functional preferences. If we are to fully understand attribute preferences, and summarized attribute preferences in particular, we need to take seriously the question of how summarized attribute preferences are formed and what they predict.

Attitudes towards Objects and Attributes

Our questions about how people form summarized attribute preferences and what these abstracted preferences might predict can be situated in the context of the social psychological literature on attitudes. Common definitions of *attitude* in this literature include "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly & Chaiken, 1993, p. 1) and "associations between a given object and a given summary evaluation of the object" (Fazio, 2007, p. 608). The terms "entity" and "object" were surely intended to be broad enough to capture attributes such as spiciness, intelligence, and other traits or characteristics that refer to dimensional qualities. But in practice, most research in the attitude literature has focused on the antecedents and consequences of people's evaluations of people, places, and things (see Ledgerwood et al., 2018, for a review and in-depth discussion).

Scholars in the social-psychological attitudes tradition might begin with the reasonable assumption that our knowledge base on attitudes towards objects would generalize to attitudes towards attributes. In other words, the vast literatures on persuasion, attitude structure, attitude strength, direct vs. indirect measurement, and so forth—literatures that have been honed by studying attitudes toward objects ranging from social groups to comprehensive exams to squirrels (e.g., Roskos-Ewoldsen & Fazio, 1992; Chaiken & Ledgerwood, 2012)—should apply to attitudes towards attributes like spiciness, intelligence, and brightness. Although this is a reasonable starting assumption, it is worth differentiating attitudes towards objects and attributes for at least two reasons.

First, there is a central theoretical perspective in this literature that posits distinct roles for attitudes towards attributes and attitudes towards objects. In classic expectancy-value models of attitude formation and change (Anderson, 1971; Fishbein & Ajzen, 1975; Lampel & Anderson, 1968), a person's attitude toward an attribute is positioned as an antecedent of (and is therefore distinct from) their attitude towards an object. In these models, an attitude toward an object depends on (a) the extent to which various attributes characterize the object (i.e., expectancy) and (b) the person's evaluations of these attributes (i.e., value, classically measured as a summarized attribute preferences). For example, a person's attitude toward an apartment might depend on (a) the extent to which they believe the apartment is bright, spacious, and centrally located and (b) the extent to which they positively evaluate the attributes of brightness, spaciousness, and centrality of location in an apartment. Notably, whereas extensive research has investigated the precursors of expectancy beliefs (e.g., Fishbein & Ajzen, 1975; Kaplan, 1973), very little research has investigated the precursors of attribute preferences: Attempts to examine causes of attitudes towards attributes are uncommon, perhaps because these attitudes initially proved resistant to manipulation attempts (Eagly & Chaiken, 1993; Eastwick et al., 2019; Lutz, 1975). In other words, we do not know much about what changes people's attribute preferences.

Second, objects and attributes are conceptually distinct because attributes—but not objects—contain their own natural contrast (Ledgerwood et al., 2018). Because attributes are dimensions, a given attribute contains a higher versus lower level contrast within itself (e.g., higher vs. lower levels of intelligence in a partner or spiciness in a food). Of course, objects can be contrasted with one another at a researcher's discretion (e.g., Coke vs. Pepsi or Coke vs.

Sprite), but a given object does not typically have a single natural contrast by definition in the way that attributes do. The existence of a natural contrast for attitudes towards attributes presents an additional complexity when people form novel attitudes toward attributes. Consider that the process of forming an attitude towards an object involves the weighing of positive and negative past experiences with the object (Fazio et al., 2015). Forming an attitude toward an attribute would further be informed by whether a person has (positive and negative) past experiences at *different levels of the attribute* across an array of objects. This dose-response association between the attribute and evaluative responses across objects is what we call a functional attribute preference, and it has no necessary logical parallel within the process of forming an attitude towards an object itself (Ledgerwood et al., 2018).[1]

Functional and Summarized Attribute Preferences

As discussed above, different research streams have tended to focus solely on either functional or summarized attribute preferences. Indeed, even Fishbein and Azjen (1975) focused solely on summarized preferences when assessing value, without considering the alternative possibility of using functional preferences to capture value. Furthermore, questions about summarized preferences only arise when studying humans, because humans, unlike other animals, readily exhibit summarized as well as functional preferences. For example, birds may exhibit a functional preference for vocal mimicry (i.e., vocal mimicry ability is positively

[1] Critically, the difference between functional and summarized preferences is not merely a measurement distinction (see Ledgerwood et al., 2018, for a full discussion). Just like attitudes towards objects, both types of attribute preferences can be assessed in more direct or indirect ways. For example, one can measure summarized preferences for the attribute *intelligent* using a self-reported rating scale (i.e., a more direct measure) or using the relative reaction time to positive versus negative words after being primed with the word *intelligent* (i.e., a more indirect measure). Similarly, in a measure of functional preferences, both the intelligence of the targets and participants' liking for those targets can be assessed directly (i.e., rating scales) or indirectly (i.e., reaction times). Therefore, the distinction between summarized and functional preferences is not about direct versus indirect measurement but about whether participants are evaluating the attribute as a concept in and of itself (summarized) or are experiencing their liking for the attribute as instantiated in a set of targets (functional).

correlated with mating interest), but unlike humans, they do not seem to form abstract ideas about the extent to which they like this quality in a mate. As a result, little empirical work has assessed both functional and summarized preferences, and the two have only recently been synthesized theoretically (Ledgerwood et al., 2018). Such a synthesis prompts new questions about summarized preferences as a potentially uniquely human oddity: Where do humans' abstract ideas about their preferences come from, and what do these ideas predict? The current set of studies seeks to address these questions in the context of human mate preferences.

Unique Antecedents of Summarized Preferences

Summarized preferences should be rooted in functional preferences to some extent—that is, logically, people's abstract ideas about the extent to which they like an attribute should be based on their experiences of liking for targets that vary along that attribute dimension. Indeed, many research literatures assume that they are linked (see Ledgerwood et al., 2018, for a review) and some assume that they are interchangeable (e.g., Ajzen and Fishbein, 1977). However, in the handful of studies that have measured both types of preferences, the evidence suggests that functional and summarized preferences are only modestly related. In correlational studies with participants evaluating photographs of potential partners, functional and summarized preferences exhibit positive, small-to-moderate correlations (Brumbaugh & Wood, 2013; Caruso et al., 2009; DeBruine et al., 2006; Eastwick & Smith, 2018; Wood & Brumbaugh, 2009). For example, in the largest of these studies, estimates of the correlations between functional preferences and summarized preferences across various traits ranged from $r = .02$ to $r = .38$ (Brumbaugh & Wood, 2013). These low-to-moderate correlations present a puzzle: Even though a person's functional preference (i.e., *actual* experienced liking for an attribute) would be a highly relevant piece of information for generating a summarized preference judgment (i.e., *beliefs* about liking for an attribute), correlations of the magnitude documented by Brumbaugh and Wood (2013) suggest that participants seem to draw from their functional preferences to only a modest extent. If people do not rely exclusively on their experienced functional preferences when abstracting a summarized preference, what other sources of information are they drawing from? What other factors might be shaping people's ideas about liking?

We suggest that, to the extent that people learn about their summarized preferences from their past experiences, this learning process may be similar to the process of inferring abstract associations from case-by-case experiences in covariation detection tasks (sometimes called "contingency learning tasks;" Allan & Jenkins, 1980; Jenkins & Ward, 1965; Mandel & Lehman 1998; see also Perales et al., 2005; Fiedler et al., 2009). Drawing from this rich literature allows us to identify extraneous contextual inputs that may influence summarized preferences.

In a typical covariation detection task, participants encounter a series of trials in which cues and outcomes vary and then make an abstract inference about the nature of the association between a cue and an outcome. For example, participants might encounter a series of trials in which a chemical is present or absent (cue) and bacteria survive or not (outcome; Allan et al., 2005). Participants would then make an overall judgment about the relation between the chemical's presence and bacterial survival. In such studies, participants' abstract judgments are regularly influenced by features of the learning context that are orthogonal to the actual experienced association between cue and outcome. One critical contextual influence is the probability or "density" of the outcome itself (i.e., whether the outcome is encountered more or less frequently in the series of trials). For example, when the probability of bacterial survival is generally high (vs. low), participants tend to infer a stronger relation between the chemical and bacterial survival, even though the actual experienced association between cue and outcome is identical across conditions. This contextual effect of outcome probability on abstract contingency inferences has been dubbed the *outcome density bias* (e.g., Blanco, 2017; Blanco et al., 2013; Matute et al., 2015; Vadillo et al., 2013, 2016).

The process of translating a functional to summarized preference is likely similar to the mental abstraction process that participants use in a typical covariation detection paradigm (see also Eastwick et al., 2019). In both cases, people experience an association (between cue and outcome or between attribute and target evaluation) and then make an abstract judgment about the strength of that association. For example, a person might experience greater romantic liking for potential partners who are higher in intelligence, and then make an abstract judgment about how much they like intelligence in a romantic partner. Thus, when inferring a new summarized preference, people may be influenced by the same contextual factors that influence covariation detection judgments, such as the density of the outcome—in this case, the average positivity of the evaluations people are experiencing. In other words, when targets are more (vs. less) likeable on average, people experience more positive evaluations and thus may infer stronger summarized preferences for an attribute even when functional preferences (i.e., the actual association of levels of that attribute with liking) are constant.

H1: Summarized preferences for an unfamiliar attribute will be more positive in a learning context with high versus low likeability targets.

Although this prediction about a contextual input for summarized preferences seems sensible, it is worth considering that forming summarized preferences is different from detecting covariation in a typical paradigm in important ways. First, in a typical covariation detection paradigm, cues and outcomes are binary: They are either present or absent (for exceptions that used continuous cues/outcomes, see Chow et al., 2019; Marsh & Ahn, 2009). In contrast, in the domain of preferences, both traits and liking typically exist on a continuum. For example, a potential partner's level of confidence can continuously range from very low to very high, and a person's evaluation of the partner could also continuously range from strongly negative to strongly positive. Second, in typical covariation detection paradigms, the actual association between cue and outcome is solely determined by the experimenter: Participants' experiences are tightly controlled to be identical. In contrast, people naturally experience their own evaluative responses in the real world, and these responses vary from person to person. Therefore, it is unclear whether the causal influence of outcome density or other contextual factors on abstract judgments would emerge in realistic, complicated contexts where people are learning about their own summarized preferences. Because of these differences, it is possible that the effect of outcome density observed in covariation detection tasks—which typically use binary variables and tightly controlled cue-outcome associations—will not appear when people make inferences about their summarized preferences.

Unique Consequences of Summarized Preferences

If the antecedents of summarized preferences include incidental contextual inputs like the average likeability of a set of targets, researchers may wonder if functional preferences reflect people's "real" attribute preferences. Are summarized preferences simply crude and noisy proxies for functional preferences? Indeed, this argument has been levied against summarized preferences in past research (Eastwick & Finkel, 2008; Brumbaugh & Wood, 2013). On the one hand, such an argument is supported by the fact that functional preferences represent people's experienced evaluations of attributes; they capture the rich and complex information manifested across various encountered objects in reality. In contrast, summarized preferences require that people simplify the rich, complex information represented in functional preferences into a single, overall summary judgment. Arguably, researchers studying human mating moved from measuring functional preferences (used in the non-human mating literature; e.g., Thornhill, 1983) to measuring summarized preferences (used in almost all studies of human mate preferences; e.g., Fletcher et al., 1999) because directly asking people about their summary judgments is a quick-and-easy measurement option when studying humans. But if summarized preferences tend to capture incidental aspects of the learning context, one could argue that researchers should always measure functional preferences unless it is too onerous to do so.

On the other hand, this view of summarized preferences as simply a poor and potentially contaminated measure of functional preferences might be overly simplistic. Considerable research suggests that abstract representations guide decision-making at a distance (Gilead et al., 2020; Trope & Liberman, 2010), and recent theoretical work suggests that summarized preferences are relatively abstract (Ledgerwood et al., 2018; Ledgerwood et al., 2020). Drawing on these ideas (which we discuss in more detail before Study 2), we posit that one purpose of summarized preferences that distinguishes them from functional preferences is that summarized preferences enable humans to select into situations at a distance, without having to directly experience those situations. We will therefore test whether summarized preferences predict how people respond to situations they have not yet directly experienced (e.g., situations learned about only through verbal communication with others).

H2: Summarized preferences will predict situation selection at a distance (i.e., deciding on situations before directly encountering them).

The Current Research

In the current research, we investigated the antecedents and consequences of summarized preferences for partner attributes. We situated our studies in the context of mate preferences—an area in which attribute preferences have been extensively studied—because mate selection exemplifies a real-life, complex process in which people develop and frequently express summarized preferences. We developed paradigms that enabled us to examine both the formation of summarized preferences (Studies 1–2), as well as the downstream consequences that summarized and functional preferences predict (Studies 2–4). In Studies 1–3, participants learned about their preferences for an unfamiliar attribute displayed in a series of preferred-sex target faces. In Study 4, we measured participants' existing summarized preferences for familiar attributes.

Across these studies, we tested our two hypotheses. First, drawing from the covariation detection literature, we examined the possibility that outcome density—in this case, the average level of liking experienced toward a set of preferred-sex targets—could be a contextual input for summarized preference formation without affecting functional preferences. We predicted that experimentally manipulating a set of target faces to be more (vs. less) likeable would lead participants to infer stronger summarized preferences for an unfamiliar attribute, even if functional preferences remained the same (H1; Studies 1 and 2; see also Study S1). In other words, participants might (mistakenly) infer that they like an attribute more when they happen to learn about their preference in a context that elicits more (vs. less) liking for the targets, even if the average association between the attribute and liking (i.e., participants' averaged functional preference) is held constant across conditions.

Second, we examined whether summarized preferences might predict decisions about situations that people learn about through socially acquired knowledge, before personally experiencing the situation directly. That is, when people learn about a novel situation from others (as when people read a description of a dating website that features partners high on intelligence or athleticism), their summarized preferences might predict the situation they select. Therefore, we hypothesized that summarized preferences would predict situation selection when participants encounter a description of a novel situation involving an opportunity to date romantic partners high on particular attributes (H2). We tested this hypothesis for both an unfamiliar attribute preference in a tightly controlled learning context (Studies 2–3) and for existing attribute preferences in a more realistic online dating context (Study 4).

In the supplemental materials, we report additional data on H1 (Study S1), a study that validated the measures used to assess romantic interest (Study S2), and a pilot study that collected norming data on the stimuli used in Study 4 (Study S3). These studies are ancillary to the main set of studies; we refer to them below when relevant to the main studies.[2]

Following recent calls to constrain researcher degrees of freedom using analysis plans (Nosek et al., 2018; Ledgerwood, 2018), we set and recorded ahead of time (and for Studies 3 and 4, publicly preregistered) our analysis plans, including power analyses, target sample size, inclusion and exclusion criteria, and planned data analyses. Additional analyses that were not planned ahead of time are reported as such below.

Study 1

We began by designing a paradigm that would allow us to examine how people initially form summarized preferences. We created a context in which participants learned about an ostensibly unfamiliar facial characteristic named "Reditry." In fact, Reditry was babyfacedness;

[2] In all studies, we also calculated the correlation between functional and summarized preferences to test whether these constructs correlated in the range observed in prior studies (e.g., $r = .02–.38$; Brumbaugh & Wood, 2013). For the unfamiliar attribute *Reditry* in Studies 1-3 and Study S1 in the Supplemental Materials, the meta-analytic functional-summarized correlation was: $r = .12$, $z = 3.74$, $p < .001$, 95% CI [.06, .18], $N = 1046$). In Study 4, which used familiar attributes depicted in photographs, the correlation between functional and summarized preferences for *intelligence* was $r = .18$, $p < .001$, 95% CI [.10, .26], and the correlation between functional and summarized preferences for *confidence* was $r = .08$, $p = .045$, 95% CI [.002, .17]. These results are consistent with the notion that individuals base their summarized preferences in part on their functional preferences, though perhaps only modestly so.

we gave this visible attribute an unfamiliar name to bypass any pre-existing semantic associations that participants might have with the term babyfacedness (i.e., participants are never made aware that Reditry = babyfacedness). In other words, using an unfamiliar name ensured that participants' summarized preferences about Reditry would be based on experiences within the experimental paradigm, rather than ideas about liking developed in prior contexts.

In the experimental paradigm, participants saw a series of real faces from the Chicago Face Database (CFD; Ma et al., 2015). We told participants how much Reditry each face had and asked them to report their liking for each face. After participants experienced their liking for the entire series of faces with varying levels of Reditry, participants reported their overall, summarized preference for Reditry.

To clarify the analogy to a typical covariation detection study: The level of Reditry is akin to the "cue" (i.e., chemical level), liking is akin to the "outcome" (i.e., bacterial survival), and participants' task is to ascertain the extent to which these two variables covary (Allan et al., 2005; Eastwick et al., 2019; Vadillo et al., 2016). Thus, a test of whether participants' summarized preferences for Reditry is informed by the average likeability of the targets (H1) is analogous to a test of whether outcome density has a biasing effect in this particular learning context.

Method

Participants and power. One hundred and seven participants completed the study online through Amazon's Mturk platform. They were randomly assigned to one of two between-subjects conditions (low average likeability vs. high average likeability). We decided *a priori* to target a cell size of 50 participants per cell based on our lab's standard practice for minimum cell size when we are not sure what effect size to expect in a new line of research (the total number of completed surveys in Qualtrics ended up being slightly higher).

We decided to use female faces as stimuli in our first study, for simplicity. Because the study measured participants' romantic liking for the faces, we limited participants to those who reported being primarily attracted to women and who were 18–35 years old to match the apparent age range of our stimuli. We set and recorded the following *a priori* exclusion criteria: We would exclude participants who (1) gave an identical rating to all faces presented for measurement of functional preferences, and/or (2) provided a nonsensical response to a Winograd-like schema designed to filter out bots or inattentive participants. The numbers of participants who met each of these exclusion criteria were 4 and 9, respectively, resulting in a final sample of $N = 94$ (26 women, 67 men, and 1 person who chose another option; $M_{age} = 27.9$, $SD = 4.5$; 60.6% White, 13.8% Asian or Pacific Islander, 8.5% Black or African American, 7.4% Hispanic or Latino only, 2.1% American Indian or Alaskan, 4.3% mixed race or multiracial; all self-reported residents in the USA).

A sensitivity power analysis in G*Power ($\alpha = .05$; Faul et al., 2007) indicated that this sample size provided 80% power to detect a difference between conditions of $d = 0.58$ (H1), and 60% power to detect a difference of $d = 0.46$. For reference, the median effect size in social psychology has been estimated at approximately $d = 0.43$ (Richard et al., 2003).

Procedure. Participants first completed a brief prescreen in which they indicated their age, gender, and whether they were primarily attracted to men or women. Only participants who were between 18 and 35 years old and primarily attracted to women were able to proceed. Next, participants saw the following instructions, adapted from Eastwick et al. (2019):

> In this study you will evaluate a series of faces that vary (from 0 to 100) in a characteristic called Reditry. Please pay careful attention to the information you

> see in this study, because we will ask you questions about it later on. Try to get an idea of your likes and dislikes, as well as how much Reditry each person has.

Participants then saw a series of 24 female faces, each presented along with its level of Reditry, and rated their romantic liking for each pictured person. After the trials, participants completed a measure of their overall summarized preference for Reditry. Lastly, after seeing another survey unrelated to the current research questions, participants completed the attention check and a demographic survey.

Materials and measures.

Stimuli. We selected 48 White female faces from the CFD (Ma et al., 2015). To manipulate average likeability, we divided the faces into two sets of 24 faces that varied similarly in babyfacedness (according to the norming-data ratings in Ma et al., 2015) and that differed only in how likeable they were on average. Likeability of these faces was rated in a previously published sample (Eastwick & Smith, 2018), in which 677 participants who were primarily attracted to women evaluated each face on a measure of romantic likeability using 1-7 rating scales. The faces we chose for the high likeability condition had a mean of $M = 3.11$ ($SD = 0.60$) on this scale, and the faces we chose for the low likeability condition had a mean of $M = 2.10$ ($SD = 0.59$). To avoid unintentionally manipulating the strength of the association between babyfacedness and likeability, we ensured that the correlations between the Ma et al. (2015) ratings of babyfacedness and the Eastwick and Smith (2018) ratings of likeability were similar across conditions ($r = .24$ in both conditions); we also checked that this correlation was similar to the correlation between babyfacedness and likeability in the full population of White female faces in the CFD ($r = .28$). Finally, we inspected the scatterplot between these two variables in both conditions to ensure that they only differed in mean likeability; for example, the means, SDs, and ranges of babyfacedness were as similar as possible across conditions, the SDs and ranges of likeability were as similar as possible across conditions, and neither condition exhibited odd distributional properties (see Figure 1).

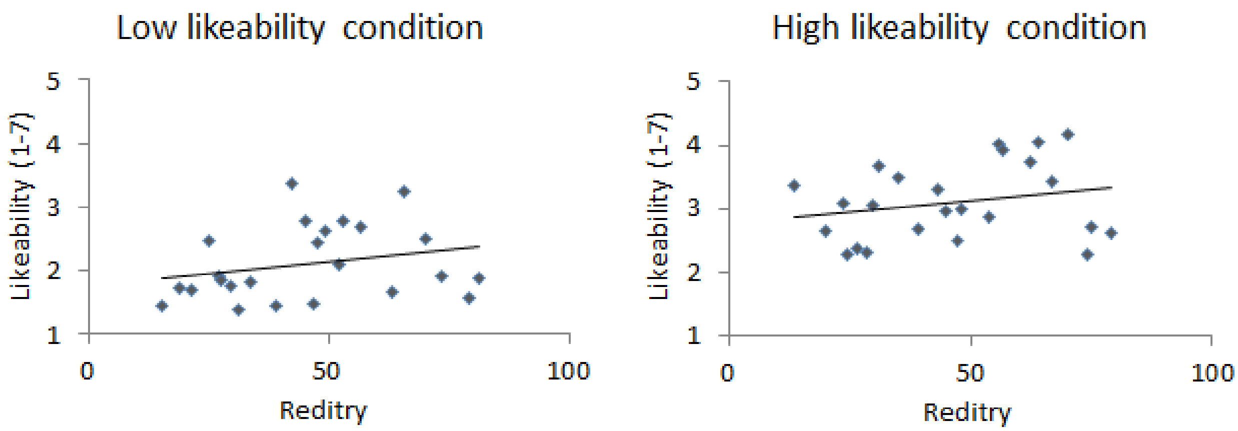

Figure 1. Scatterplots of the stimuli used for Study 1; each dot represents a face target. Notice that the correlation between pretest ratings of likeability and Reditry is the same in both conditions (i.e., the slopes of the trend lines were the same), whereas the average likeability is higher in the high (vs. low) likeability condition (i.e., the intercept of the trend line in the high vs. low likeability condition was higher).

After creating the two sets of faces, we rescaled the CFD rating of each face's babyfacedness to a value ranging from 0–100 and presented it to participants as the Reditry value of that face.

Functional preference measure. Following Wood and Brumbaugh's (2009) method, we measured participants' functional preferences for Reditry as the association between the level of Reditry in the 24 targets with participants' experienced liking for those targets. On each screen, participants saw one target accompanied by the Reditry value of that face. They rated their experienced romantic liking for each target in response to the prompt "To what extent are you romantically interested in this person?" on a 9-point Likert-type scale (from -4 = *strongly dislike* to 4 = *strongly like*).[3] Presentation order of the targets was randomized.

[3] We used the term "romantic interest" rather than simply "liking" to ensure correspondence between the functional preference measure and the summarized preference measure, such that both assessed liking for Reditry in a romantic

Participants' functional preferences were calculated following Wood and Brumbaugh's procedures: First, each participant's romantic interest ratings were rescaled to a percentage-of-maximum-possible (POMP; Cohen et al., 1999) metric ranging from 0 to 100, such that 0 indicated the scale floor (*strongly dislike*) and 100 indicated the scale ceiling (*strongly like*).[4] Next, the POMP-rescaled ratings were regressed onto the levels of Reditry. Finally, the standardized regression coefficients from the regression models, akin to within-person slopes in linear mixed models, were r-to-z transformed (Fisher, 1925) to normalize the distributions for analysis. Each transformed regression coefficient represents a participant's own functional preference for a given attribute.

Summarized preference measure. After participants experienced their liking for all 24 faces, we measured their overall summarized preferences for Reditry with two items: "How much do you like Reditry in a romantic partner?" (from -4 = *strongly dislike* to 4 = *strongly like*) and "How desirable to you is Reditry in a romantic partner?" (from -4 = *extremely undesirable* to 4 = *extremely desirable*). We averaged ratings on these two items to form an index of summarized preferences for Reditry (α = .92).

Winograd-like schema. We included an attention check that involved text interpretation to filter out bots and mindlessly responding participants, based on the structure of a Winograd schema (used to assess human-like reasoning; Levesque et al., 2011). Participants saw a short story: "Santa Claus is on vacation, and he goes to a beautiful beach on the Brazilian coast. He

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context (Ajzen & Fishbein, 1977; Ledgerwood et al., 2018); if we simply asked participants to report "liking," they might report liking for the targets as potential friends rather than as potential romantic partners. As measures of romantic evaluation, the terms "interest" and "liking" are interchangeable. In Study S2 (reported in the supplemental materials), items assessing romantic interest ("to what extent are you romantically interested…") and romantic liking ("to what extent do you romantically like…") were strongly associated, β = .93, 95% CI [.92, .94].

[4] Note that because we ran a standardized regression after the POMP transformation, the end result is the same as that without the POMP transformation. We followed this procedure to be consistent with previous research (e.g., Wood & Brumbaugh, 2009).

realizes he has forgotten sunscreen and wonders how he can protect his skin. Luckily, a young kid nearby understands the situation right away. As he wants to receive a nice gift for Christmas, he lends him a beach umbrella." Next, they answered two open-ended questions about the story ("Who receives the beach umbrella?" and "What does the kid hope will happen in December?"). Participants were excluded if they gave nonsensical answers (e.g., "brazilian"), as coded by a researcher without knowledge of how exclusion would affect any study results.

Results

Manipulation check. We checked whether the manipulation of average target likeability successfully influenced the amount of liking that participants experienced when learning about their preferences. Our manipulation of average target likeability was successful: On average, participants in the high likeability condition experienced more liking for the faces they saw (M = -0.53, SD = 1.23) than participants in the low likeability condition (M = -1.67, SD = 1.35), $t(92) = 4.29$, $p < .001$, $d = 0.95$, 95% CI [0.52, 1.37].[5] Note that in general, romantic liking for these faces was on the lower side of the scale, which presumably reflects the fact that the CFD was designed to provide carefully controlled experimental stimuli (e.g., neutral expressions, minimal to no makeup) rather than to attract romantic partners.

Functional preferences for Reditry. Although we took care to ensure that the correlation between Reditry and pretest ratings of face likeability were similar across conditions, it is still possible that our manipulation of average likeability could unintentionally influence participants' experienced functional preferences for Reditry. Thus, it was important to assess whether participants' experienced functional preferences for Reditry differed between the two conditions. Functional preferences were very similar across the two conditions (M = 0.24, SD =

[5] For this and all subsequent t-tests, we report Student's t-test for ease of interpretation; Welch's t-test yielded identical conclusions in all cases.

0.26 vs. $M = 0.20$, $SD = 0.15$ for the high and low likeability conditions, respectively), $t(92) = 0.91$, $p = .365$, $d = 0.19$, 95% CI [-0.22, 0.59], consistent with the assumption that our manipulation of average target likeability did not affect participants' functional preferences for Reditry.

Main analyses. After confirming that our manipulation was successful at influencing average liking but not functional preferences for Reditry, we proceeded to our main analysis. We tested whether average likeability of the targets influenced summarized preferences for Reditry (H1). Indeed, participants inferred stronger summarized preferences for Reditry in the high versus low likeability conditions ($M = 0.18$, $SD = 1.74$ vs. $M = -0.89$, $SD = 1.84$), $t(92) = 2.88$, $p = .005$, $d = 0.60$, 95% CI [0.18, 1.01]. In other words, participants inferred that they liked Reditry substantially more when they learned about their preference in a context with high (vs. low) likeability targets. The CI was compatible with a broad range of effect sizes, suggesting additional data would be informative.

Discussion

The results of our first study suggest that when participants formed summarized preferences for an unfamiliar attribute, they based their summarized preferences on the average liking they experienced in the learning context (H1). Recall that we originally derived this hypothesis by noting the similarities between (a) the process of forming a summary evaluation of an unfamiliar attribute, and (b) the typical covariation detection paradigm (Vadillo et al., 2016). That is, our participants had to ascertain how a cue (i.e., Reditry level) was related to an outcome (i.e., their liking for the target) across a set of targets, and so we hypothesized that the outcome density bias might play a role in summarized preference formation in the same way that it emerges in covariation detection studies.[6] The results of this first study suggest that this connection between disparate literatures may indeed be useful.

At a broader level, these results suggest that people might form summarized preferences by drawing on seemingly incidental aspects of the learning context, independently from their actual functional preferences for that attribute. This finding then begs the question: If summarized preferences can be uniquely influenced by incidental features of the learning context, then is there any reason for researchers to study summarized preferences? As noted in the introduction, some researchers have argued that summarized preferences are simply crude proxies for functional preferences (Eastwick & Finkel, 2008; Brumbaugh & Wood, 2013), and our Study 1 results could be interpreted as consistent with this idea.

We see reasons to pause before accepting this conclusion. Even if people were to form some summarized preferences without drawing from their experienced functional preferences at all, summarized preferences may have some predictive power. In particular, one purpose of summarized preferences may be that they enable people to select into situations at a distance, based on socially acquired knowledge. Because summarized preferences are abstract ideas about likes and dislikes that are not tethered to any particular circumstance, they should be particularly useful when people are deciding on situations they have yet to encounter, without having to first experience those situations directly. In Study 2, we began to probe the possibility that summarized preferences can predict some interesting downstream consequences by including an additional item measuring situation selection at a distance.

Study 2

[6] Note that the question of learning how much one likes the attribute Reditry is not the same as learning what facial features cause a face to be high or low in Reditry. Our study is focused on the former *evaluative* process; the latter *attributional* process is fascinating, too (and better studied; see Jaeger & Jones, 2020; Zebrowitz & Montepare, 2008), but it was not the focus of the current investigation.

Study 2 sought to replicate and extend Study 1 in several ways. First, we created a new version of our paradigm with White male faces rather than White female faces, both to verify that our Study 1 results generalized beyond just White female faces and to disentangle two possible explanations for our Study 1 results. One possible explanation for the effect of average likeability on summarized preferences is the outcome density bias, as described in the introduction. However, it may also be possible to explain these results using a feature positive-effect account (Fazio et al., 1982; Jenkins & Sainsbury, 1970; Newman et al., 1980; Ward & Jenkins, 1965). Recall that in Study 1, participants displayed a positive functional preference for Reditry: On average, participants experienced greater liking for the female faces as babyfacedness increased. This positive functional preference meant that participants in the high (vs. low) likeability condition experienced more instances where they liked a high Reditry face. Insofar as people focus more on what happens in the presence rather than the absence of the feature (i.e., high Reditry), it seems possible that participants in the high (vs. low) likeability condition inferred a stronger preference for Reditry simply because they noticed more instances in which they liked high Reditry faces. However, in a context where functional preferences are neutral (i.e., near-zero), the feature-positive "high Reditry, high likeability" faces should be equally common in the two conditions. Thus, if the same pattern of results were to appear when functional preferences are neutral, it would suggest that outcome density bias is a more likely mechanism than the feature positive effect. Because functional preferences for babyfacedness in male faces are near zero ($r = .01$ for White male faces in the CFD), using male faces allowed us to disentangle these two possible accounts. We hypothesized that average likeability would influence summarized preferences for Reditry (H1), even when functional preferences for Reditry were neutral.

Second, we also began to probe the possibility that summarized preferences predict situation selection at a distance. By means of socially acquired knowledge, humans have a profound ability to learn, communicate, and make decisions about situations at a distance before actually entering and personally experiencing them. Ancestrally, a hunter could decide which fields to visit based on someone's description of the characteristics of available prey; in modern times, a person can decide whether to try a new bar based on reviews that describe the patrons as particularly fun-loving or attractive. In the realm of online dating, platforms like The League and Sapio tout the high intelligence of their memberships (Murdoch, 2017), and people can decide whether to sign up for these websites based on socially acquired knowledge (e.g., verbal descriptions provided by others rather than their own direct experiences).

Theory and research suggest that abstract representations provide a crucial cognitive toolkit that humans can use to make future plans and navigate decision-making at a distance (Gilead et al., 2020; Fujita, 2011; Hofmann & Kotabe, 2012; Leary & Buttermore, 2003; Soderberg et al., 2015; Trope & Liberman, 2010; Wakslak et al., 2008). Importantly, summarized preferences are relatively abstract: They reflect people's generalized evaluations of a trait, abstracted away from any one particular target or experience (Eastwick et al., 2019; Ledgerwood et al., 2018; Ledgerwood et al., 2020). Thus, it follows that summarized preferences, like other abstract representations, may enable people to make decisions about situations they have not yet directly experienced (H2). To begin probing this possibility, we added a new item to measure participants' interest in a dating website that was described as providing access to partners high in Reditry (i.e., a relevant situation that participants learned about through socially acquired knowledge—a verbal description—rather than direct experience). We hypothesized that summarized preferences for Reditry would predict participants' interest in joining this described website (H2).

Method

Participants. One hundred and eighty-four participants completed the study online through Mturk. Participants were randomly assigned to one of two conditions (low average likeability vs. high average likeability). An *a priori* power calculation in G*Power (Faul et al., 2007) suggested that to have 95% power to detect the effect size of d = .60 observed for our focal test of H2 in Study 1, we would need a total sample size of 148. We decided *a priori* to target a sample size of 170 with the goal of having at least N = 150 after planned exclusions; our actual total sample reached N = 180 because our survey software failed to count 10 participants with usable data who did not click to the last page of the survey. We used the same *a priori* exclusion criteria from Study 1. In this study, six participants gave the same ratings to all targets, and seven participants failed the attention check, resulting in a final sample of N = 167 (139 women, 21 men, and 7 people who chose another option; M_{age} = 27.4, SD = 4.8; 71.3% White, 7.2% Asian or Pacific Islander, 7.2% Black or African American, 10.2% Hispanic or Latino only, 4.0% mixed race or multiracial, 4% reported a different identity or preferred not to answer; all self-reported residents in the USA).

Procedure. The procedure was identical to Study 1 except for two changes: (1) We used male faces instead of female faces and (2) we added an additional dependent measure as a first attempt to assess situation selection at a distance.

New materials and measures.

Stimuli. Similar to Study 1, we selected 48 White male faces from the CFD (Ma et al., 2015) and divided them into two sets of 24 faces that varied similarly in babyfacedness and differed only in how likeable they were on average. Based on ratings provided by 665 pretest participants who were primarily attracted to men (Eastwick & Smith, 2018), the average likeability of faces in the high likeability condition was $M = 2.76$ ($SD = 0.59$), and the average likeability of faces in the low likeability condition was $M = 1.83$ ($SD = 0.38$). We again ensured that the correlation between pretest ratings of babyfacedness and likeability was similar across conditions ($r = .05$ in both conditions) and reflected the actual correlation in the full population of White male faces in the CFD ($r = .01$). Again, we inspected the scatterplot between these two variables in both conditions and compared the descriptives to ensure that they only differed in mean likeability (see Figure 2).

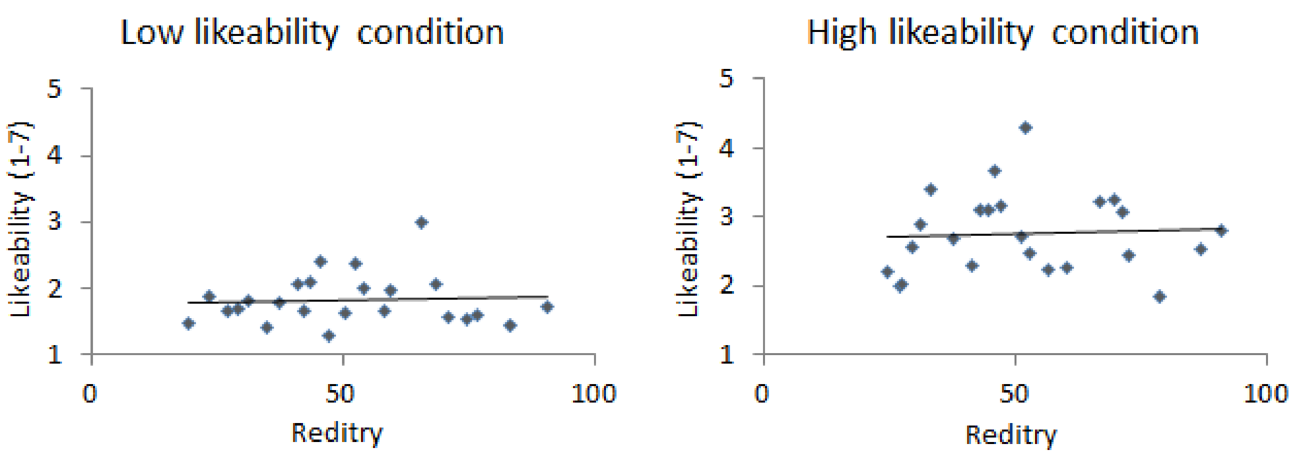

Figure 2. Scatterplots of the stimuli used for Study 2; each dot represents a face target. Notice that the correlation between pretest ratings of likeability and Reditry was neutral in both conditions (i.e., the slopes of the trend lines were the same), whereas the average likeability was higher in the high (vs. low) likeability condition (i.e., the intercept of the trend line in the high vs. low likeability condition was higher).

Measure of situation selection at a distance. After completing the same functional and summarized preference measures used in Study 1, participants read a description of a situation that would provide them with access to potential partners high in Reditry: "Imagine that you are single and looking for a romantic partner. Imagine also that there is a dating website designed for people looking for partners high in Reditry. If you joined this website, you would have access to potential partners who are in the top 30% of Reditry." We asked participants how interested they would be in this website that would only include partners high in Reditry. Participants rated their interest on a 9-point Likert-type scale (1 = *not at all interested* to 9 = *very interested*).

Results

Manipulation check. Our manipulation of average target likeability was successful: On average, participants in the high likeability condition liked the faces they saw more (M = -0.80, SD = 1.23) than participants the low likeability condition (M = -1.87, SD = 1.37), $t(165) = 5.32$, $p < .001$, d = 0.82, 95% CI [0.50, 1.14].

Functional preferences for Reditry. We compared functional preferences for Reditry across the two conditions to check whether our manipulation of average target likeability unintentionally influenced average functional preferences for Reditry. Functional preferences were very similar across the two conditions (M = 0.12, SD = 0.26 vs. M = 0.10, SD = 0.24), $t(165) = 0.53$, $p = .599$, d = 0.08, 95% CI [-0.22, 0.38].

Main analyses. After confirming that our manipulation was successful at influencing average liking but not average functional preferences for Reditry, we proceeded to our main analyses. First, we tested whether average likeability of the targets influenced summarized preferences for Reditry (H1). Replicating Study 1, participants inferred stronger summarized preferences for Reditry in the high versus low likeability conditions (M = -0.34, SD = 1.92 vs. M = -1.00, SD = 1.91), $t(165) = 2.23$, $p = .027$, d = 0.34, 95% CI [0.04, 0.65].

Finally, we tested whether summarized preferences for Reditry predicted situation selection at a distance (H2) by regressing interest in joining the dating website on participants' summarized preferences. Summarized preferences significantly predicted interest in the website, b = 0.62, SE = 0.08, $p < .001$, r = .53, 95% CI [.42, .63], providing initial evidence that summarized preferences might predict situation selection at a distance. Interestingly, functional preferences did not predict interest in joining the website, $b = 0.93$, $SE = 0.69$, $p = .180$, $r = .10$, 95% CI [-.04, .25]; we test this effect with stronger methods in Studies 3 and 4.

Discussion

The results of our second study replicated and extended Study 1, providing more evidence that when participants formed summarized preferences for an attribute for the first time, they based their summarized preferences on the average liking they experienced in the learning context (H1). Importantly, our manipulation of average likeability influenced participants' summarized preferences not only when average functional preferences for Reditry were positive (for female faces, in Study 1), but also when average functional preferences for Reditry were neutral (for male faces, in Study 2). This pattern of results is consistent with outcome density rather than feature positivity as the underlying mechanism for the results observed in Study 2. Although feature positivity could still partially explain the Study 1 results, given that Study 1 sampled from a different population of participants (i.e., participants primarily attracted to women rather than men), the consistency of results across Studies 1–2 makes the feature positivity account less parsimonious and less likely. In either case, the results of these studies provide support for the striking conclusion that people's summarized preferences for traits can be informed by seemingly incidental aspects of the context in which they learn about those preferences.

Perhaps most intriguingly, Study 2 provides a first hint that summarized preferences—even when only weakly based on functional preferences and when influenced by incidental contextual inputs—may still predict important outcomes. Specifically, participants' summarized preferences for Reditry predicted their interest in joining a dating website for high-Reditry partners (H2). Thus, it seems possible that even when functional and summarized preferences are only weakly related, summarized preferences might have important predictive power.

Study 3

As noted earlier, scholars studying attribute preferences in the context of human mating have tended to assume either that summarized and functional preferences can be measured interchangeably (e.g., Gerlach et al., 2019; see Ledgerwood et al., 2018, for a review), or that functional preferences are superior measures and should be assessed whenever possible (e.g., Eastwick & Finkel, 2008, Wood & Brumbaugh, 2009). In contrast to both views, the current data suggest that summarized preferences may have some unique consequences. That is, summarized preferences may be useful for situation selection at a distance, when people rely on socially acquired knowledge rather than direct experience to guide their decisions about which situations to enter (H2).

Of course, one might wonder whether our Study 2 results truly show a unique consequence of summarized preferences, or whether functional preferences simply did not predict situation selection at a distance because our measure of functional preferences was a poor measure that in fact would not predict anything. In contrast, consistent with work showing that abstract mental tools are specifically recruited to support action at a distance (Trope et al., 2021), we predict that whereas summarized preferences should predict situation selection at a distance, functional preferences should predict situation selection with experience (i.e., a decision to enter a situation that participants have had an opportunity to sample). That is, once people have sampled targets from a novel situation (e.g., previewing other users on a dating website), they will (re-)experience their functional preferences during the sampling process and use those preferences to decide whether to enter the situation. For example, people can sometimes see photographs of other users on a dating website or sign up for a free trial before deciding which dating platform to use. Once again, market researchers are interested in predicting how trial periods affect consumer purchasing decisions (e.g., Lee & Tan, 2013; van der Heijden et al., 2003).

Although not the central focus of our hypotheses, we should expect that functional preferences weakly (or do not) predict situation selection at a distance and that summarized preferences weakly (or do not) predict situation selection with experience. These predictions similarly draw from the principles of compatibility and matching: Summarized and functional preferences should be less relevant and predictive when they do not match the decisions that they support. When deciding whether to select into situations at a distance, people do not have access to their functional preferences as evaluative guides (which require that people directly experience those situations), and thus functional preferences could not guide those decisions. In contrast, when deciding on situations that people can sample, the relevance of summarized preferences as an evaluative guide diminishes in the face of functional preferences: People no longer need their abstract ideas about liking when they can directly recruit their experiences of liking for decision-making. In other words, to the extent that summarized preferences represent an abstract evaluative tool that people can use to make decisions at a distance, we expect that people will use them specifically for decision-making at a distance (see e.g., Ledgerwood et al., 2010; Trope et al., 2021, for similar reasoning). Therefore, to the extent that summarized and functional preferences are weakly correlated, the predictive power of summarized and functional preferences should be dissociable.

In Study 3, we set out to test the predictive power of existing summarized and functional preferences in the context of online dating, where people often have to weigh their interest in different dating websites that may offer access to different pools of partners. We tested both our key hypothesis that summarized preferences would primarily predict situation selection at a distance (H2), as well as the corresponding hypothesis for functional preferences:

H3: Functional preferences will predict situation selection when people can directly sample a situation.

Following the measurement of summarized and functional preferences, we introduced participants to dating websites that would provide access to members who are high in Reditry. We designed our websites so that some provided participants with an opportunity to sample targets from the website (by viewing photographs of users), whereas another did not provide participants with such an opportunity (participants simply read descriptions of the website). We tested how summarized and functional preferences would respectively predict participants' website selection at a distance and website selection with experience. We preregistered our pre-analysis plan on OSF at: https://osf.io/c8p5a/?view_only=f162cf7b9b2941809c2343d230ba97a6.

Method

Participants and power. Five hundred and eighty-six participants completed the study online through MTurk. As in Studies 1–2, we limited the range of participants to 18–35 years old and primarily attracted to males. In Study 2, the correlation between functional and summarized preferences was $r = .09$, $p = .259$, 95% CI = [-.06, .24]. We planned to power this study to obtain a stable estimate of this correlation (see Supplemental Materials, section "Correlation between functional and summarized preferences"). Based on Schönbrodt and Perugini (2013), we need at least 470 participants to reach a corridor of stability of width = .10 in a 95% confidence interval. We decided to collect a larger sample size to have at least $N = 550$ after exclusions to provide a stable estimate of the effect size. We used the same *a priori* exclusion criteria from Studies 1–2.

In this study, 12 participants gave an identical response to all photographs and 4 failed the attention check, resulting in a final $N = 570$ (519 women, 42 men, and 9 a different identity; $M_{age} = 27.9$, $SD = 4.5$; 63.2% White, 10.5% Asian or Pacific Islander, 8.2% Black or African American, 7.4% Hispanic or Latino only, .05% American Indian or Alaskan, 8.8% mixed race or multiracial, 1.4% reported a different identity or preferred not to answer; all self-reported residents in the USA).

Procedure. All participants completed measures of functional and summarized preferences for Reditry, followed by the attention check. Next, we told participants that the research team was developing a series of dating websites and we asked them to indicate their interest in those dating websites. Our situation selection at a distance measure was identical to the dependent measure of Study 2. In this measure, we described a dating website as designed "for people looking for partners high in Reditry." Participants learned that if they joined this website, they would "have access to potential partners who are in the top 30% of Reditry," and they rated their interest in joining. In addition, we assessed participants' interest in selecting into situations that they had an opportunity to directly experience. In this situation selection with experience measure, participants learned about two websites, Website A and Website B, and they had the opportunity to sample these websites via an ostensible screenshot of each website presented side by side, one with faces higher in Reditry on average and the other with faces lower in Reditry on average (Figure 3). We counterbalanced the order of the two situation-selection dependent measures (i.e., at a distance vs. with experience) across participants. Last, participants provided their demographic information.

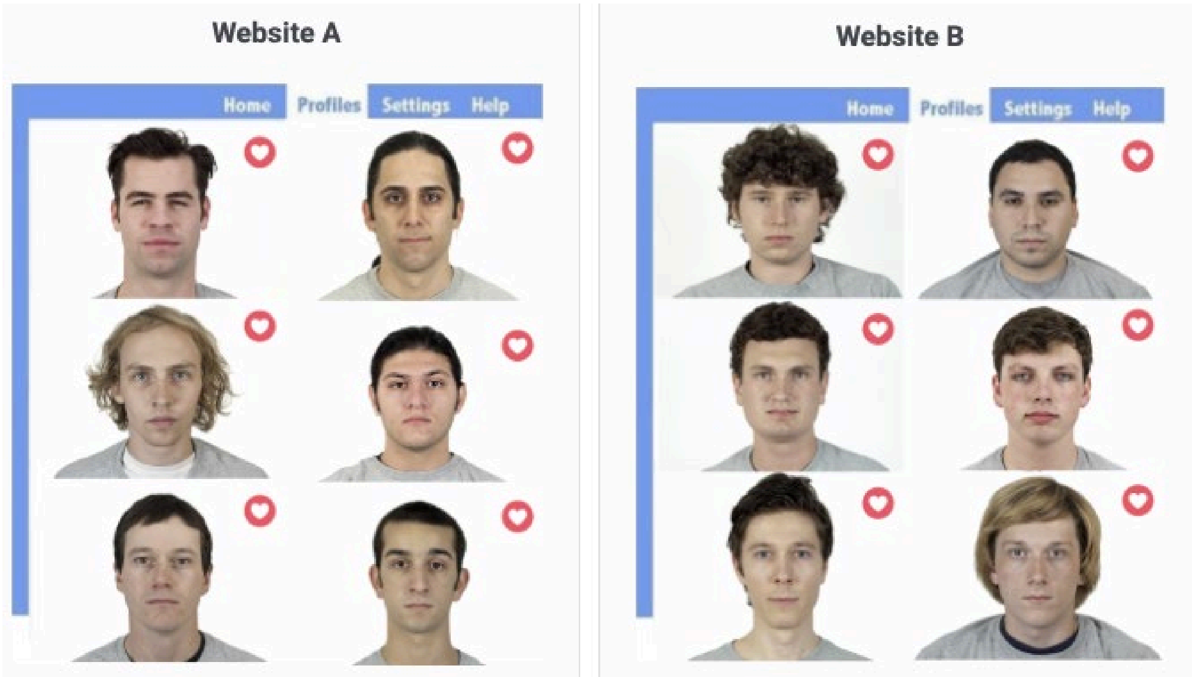

Figure 3. Stimuli used in Study 3 for the dependent measure of situation selection with experience. The screenshot of Website A presented photographs of six targets that had been rated lower in Reditry (babyfacedness), and the screenshot of Website B presented photographs of six targets that had been rated as higher in Reditry. The two websites appeared side by side on the same screen and participants selected their choice by clicking on one of the two screenshots.

New materials and measures.

Functional preference measure. Participants saw 40 White male faces from the CFD (Ma et al., 2015), one at a time. On each screen, participants saw one target accompanied by the Reditry value of that face. They rated their experienced romantic liking for each target in response to the prompt "To what extent are you romantically interested in this person?" on a 9-point Likert-type scale (from -4 = *strongly dislike* to 4 = *strongly like*). Participants' functional preferences for Reditry were calculated using the same procedure as in Studies 1 and 2.

Measure of situation selection with experience. To assess participants' interest in entering a situation with (a) partners low in Reditry or (b) partners high in Reditry after having a chance to sample targets from those situations, we presented participants with screenshots of two dating websites and asked them to indicate which website they would choose to join. The first website screenshot contained six photographs of targets that were lower in Reditry on average ($M = 1.92$, $SD = 0.22$); the second website screenshot contained six photographs of targets that were higher in Reditry on average ($M = 3.36$, $SD = 0.42$; see Figure 5). The websites were matched in attractiveness ($M = 2.74$, $SD = 0.33$ and $M = 2.74$, $SD = 0.38$, respectively).

Results

Hypotheses 2 and 3. We tested our hypotheses that summarized preferences would predict situation selection at a distance (H2), whereas functional preferences would predict situation selection with experience (H3). For this relatively complex set of analyses, we followed our pre-analysis plan to constrain researcher degrees of freedom; all analyses reported below were preregistered unless explicitly noted in the text. Because multiple analytic approaches were possible with our data, we decided *a priori* to focus on the effect sizes and *p*-values from one focal approach (structural equation modeling [SEM], as described below), which would allow us to think about those *p*-values as diagnostic of the likelihood of a given statistical result (de Groot, 2014; Nosek et al., 2018), while also considering the consistency of the patterns across alternative analytic approaches (e.g., multiple regression). In other words, we planned to calibrate our confidence in our results based on both the extent to which focal *p*-values reached significance and on the extent to which similar patterns of effect sizes emerged across different analytic approaches. We decided to focus primarily on the effect sizes and *p*-values from the SEM approach because estimates from latent variable models tend to be more accurate (less biased) than those from observed variable approaches and because an SEM approach helps avoid Type I error inflation in this multivariate context (Ledgerwood & Shrout, 2011; Wang & Eastwick, 2020). At the same time, any one estimate from SEM analyses using latent variables can be quite far from the true population parameter (Ledgerwood & Shrout, 2011), so looking for consistent patterns across multiple analytic approaches can be informative.

Our planned focal approach was therefore to use SEM to test the effect of a summarized preference on a dependent variable, while controlling for the functional preference, and vice-versa (e.g., testing the effect of summarized preference for Reditry on a dependent variable, controlling for functional preference for Reditry). In the SEM analysis, both dependent variables were simultaneously regressed on both predictors (i.e., summarized and functional preferences); the predictors were modelled as latent factors (Figure 4). Latent factors of summarized preferences had two indicators, whereas latent factors of functional preferences were indicated by fixing participants' functional preferences to the reliability of .70, as it provides a reasonable tradeoff between Type I error rate and power (Savalei, 2019; as we discuss below, results were robust to other ways of account for reliability). The SEM model provides a good fit of the data, $\chi^2(3) = 0.58$, $p = .901$, Comparative Fit Index (CFI) = 1.00, Tucker-Lewis Index (TLI) = 1.03, Root Mean Square Error of Approximation (RMSEA) = 0.00. Correlations among key variables are reported in Table A1 (Appendix).

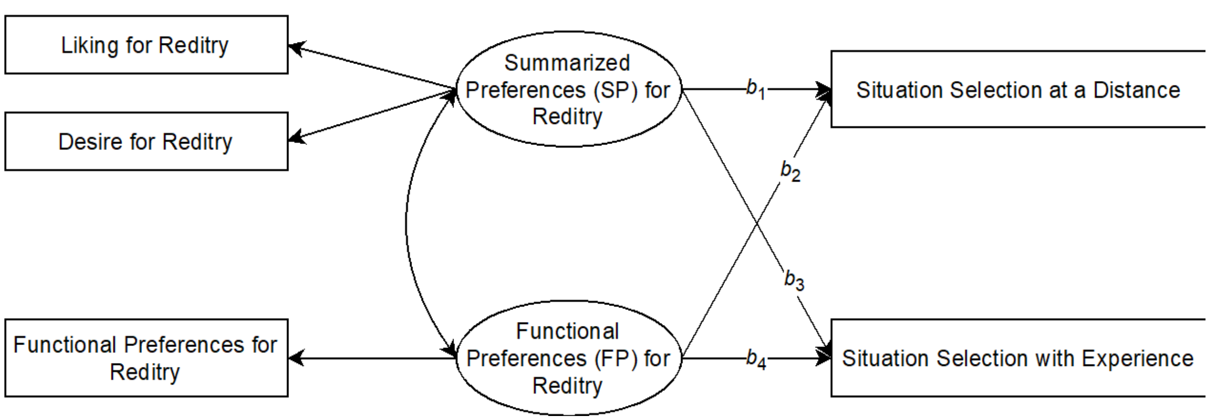

Figure 4. Diagram of the model of double dissociation in which dependent variables were regressed on attribute preferences as latent predictors. Key parameters showing the double dissociation pattern are denoted b_1–b_4 and reported in Table 1. For visual simplicity, residual

(co)variances are not shown. Higher values on both situation selection variables indicate a tendency to select into higher Reditry situations.

We also planned to model the unique effects of summarized and functional preferences by conducting multiple regressions in which each dependent variable was regressed on both types of preferences and examining the effect size estimates provided by the partial regression coefficients of the predictors. Finally, we planned to conduct simple regressions as well (i.e., one preference predicting one dependent variable).

Table 1 presents the results from all three analytic approaches. Hypothesis 2 received support, just as in Study 2: Summarized preferences significantly predicted situation selection at a distance using all three approaches (with moderate-to-large effect sizes). Also as in Study 2, functional preferences did not predict situation selection at a distance especially strongly: Only one of the three approaches was significant, and effect sizes were considerably smaller than for summarized preferences. In our focal SEM approach, summarized preferences predicted situation selection at a distance more strongly than functional preferences ($b_1 > b_2$, $\Delta\chi^2(1) = 27.46$, $p < .001$; exploratory/not planned).[7] The effect size difference between summarized and functional preferences was more or less the same across all three approaches.

Hypothesis 3 also received support. Functional preferences predicted situation selection with experience using all three approaches with modest but nevertheless significant effect sizes. Summarized preferences did not significantly predict situation selection with experience using any of the three approaches, and effect sizes were approximately zero. In our focal SEM approach, functional preferences predicted situation selection with experience more strongly than summarized preferences, although this difference was not significant ($b_4 > b_3$, $\Delta\chi^2(1) = 3.20$, p

[7] To compare the relative strength of the effects, we conducted likelihood-ratio tests by comparing the exact fit of the original model, where the regression coefficients of summarized and functional preferences were freely estimated, with that of a model with equality constraints on those regression coefficients.

= .074; exploratory/not planned). The effect size difference between summarized and functional preferences was more or less the same across all three approaches. In total, the pattern of results suggests that we can have a relatively high degree of confidence that both H2 and H3 (i.e., the double dissociation pattern) received support.

Table 1.

Summarized and Functional Preferences Predicting Primary Dependent Variables in Study 3.

Analytic Approaches	Predictor Type	Parameter	Dependent Variables	*b* (SE)	*p*	β	*OR*	*r* [95% CI]
Structural Equation Models	SP	b_1	SS at a distance	0.49 (0.05)	< .001	.41	-	.40 [.33, .47]
	FP	b_2	SS at a distance	1.00 (0.55)	.066	.07	-	.07 [-.00, .14]
	SP	b_3	SS with experience	0.02 (0.03)	.554	-	1.06	.02 [-.04, .07]
	FP	b_4	SS with experience	1.26 (0.41)	.002	-	1.39	.09 [.03, .15]
Bivariate Regression	SP	-	SS at a distance	0.48 (0.04)	< .001	.41	-	.41 [.33, .48]
	FP	-	SS at a distance	1.27 (0.50)	.011	.11	-	.11 [.02, .19]
	SP	-	SS with experience	0.05 (0.04)	.248	-	1.10	.03 [-.02, .07]
	FP	-	SS with experience	1.57 (0.47)	< .001	-	1.34	.08 [.03, .13]
Multiple Regression	SP	-	SS at a distance	0.46 (0.05)	< .001	.40	-	.40 [.32, .47]
	FP	-	SS at a distance	0.75 (0.46)	.104	.06	-	.06 [-.01, .14]
	SP	-	SS with experience	0.03 (0.05)	.453	-	1.07	.02 [-.03, .06]
	FP	-	SS with experience	1.53 (0.48)	.001	-	1.33	.08 [.03, .13]

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection, OR = odds ratio. Unstandardized regression coefficients (*b*) for situation selection with experience are logit coefficients.

Reliability of functional preferences. A reviewer noted that, given the modest number of trials in Studies 1–3, the reliability of functional preferences could be low. To investigate this concern, we first calculated the cross-product alpha (or αCP) coefficient using the multicon program in R (Sherman & Wood, 2014; Wood & Brumbaugh, 2009). The reviewer was correct: The αCP estimates were low in Study 1 with 24 female faces per condition (αCP = -.13, low likeability condition; αCP = .41, high likeability condition), Study 2 with 24 male faces per condition (αCP = .38, low likeability condition; αCP = .47, high likeability condition), and in the current study with 40 male faces (αCP = .52). These low αCP values could explain why summarized and functional preferences correlated toward the low end of the Brumbaugh and Wood (2013) range of *r* = .02–.38 (see Footnote 2).

Given these observed estimates of reliability for our functional preference measure, it seemed important to check whether the results of Study 3 are sensitive to variations from our preregistered decision to set the alpha to .70 for the functional preference latent measure in our SEM. The results were robust to variations in this research decision: Testing the model with other, lower values did not change the pattern of findings (see Table 2). In other words, even though the estimated reliability of our functional preference measure was low in this study, H3 received support anyway. Nevertheless, reliability is important for power and precision (e.g., Ledgerwood & Shrout, 2011; Wang & Rhemtulla, 2021). We use a larger number of trials in Study 4 to approximate the Wood and Brumbaugh (2009) procedure, which should produce considerably higher αCP values.

Table 2.

Study 3 results with functional preference with different values of fixed reliability.

Functional Preference Reliability	Predictor Type	Parameter	Dependent Variables	*b* (SE)	*p*	β	*OR*	*r* [95% CI]
.17	SP	b_1	SS at a distance	0.83 (0.11)	< .001	.38	-	.36 [.28, .44]
	FP	b_2	SS at a distance	0.34 (0.19)	.069	.15	-	.15 [-.01, .30]
	SP	b_3	SS with experience	-0.06 (0.08)	.481	-	0.91	-.03 [-.10, .05]
	FP	b_4	SS with experience	0.42 (0.15)	.004	-	2.06	.20 [.07, .32]
.38	SP	b_1	SS at a distance	0.88 (0.10)	< .001	.40	-	.39 [.32, .46]
	FP	b_2	SS at a distance	0.22 (0.10)	.066	.10	-	.10 [-.005, .20]
	SP	b_3	SS with experience	0.01 (0.06)	.870	-	1.02	.00 [-.05, .06]
	FP	b_4	SS with experience	0.27 (0.09)	.002	-	1.58	.13 [.05, .20]
.52	SP	b_1	SS at a distance	0.89 (0.10)	< .001	.40	-	.40 [.33, .47]
	FP	b_2	SS at a distance	0.18 (0.10)	.066	.08	-	.08 [-.005, .17]
	SP	b_3	SS with experience	0.02 (0.06)	.676	-	1.04	.01 [-.04, .06]

FP	b_4	SS with experience	0.23 (0.07)	.002	-	1.48	.11 [.04, .17]

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection, OR = odds ratio. Unstandardized regression coefficients (*b*) for situation selection with experience are logit coefficients. We report these three illustrative reliability values based on the αCP of the studies with male faces: .17 is the lower 95% CI bound of the low likeability condition in Study 2; .38 is the mean reliability estimate of the low likeability condition in Study 2; and .52 is the actual reliability estimate in Study 3 (i.e., deriving from the same data used to test the model).

Discussion

The results of Study 3 suggested that both summarized and functional preferences have predictive power. We observed a double dissociation between summarized and functional preferences, such that summarized preferences predicted situation selection at a distance (as when people read a description of a website; H2), whereas functional preferences predicted situation selection with experience (H3). The nonpredicted paths (i.e., summarized preferences predicting situation selection with experience; functional preferences predicting situation selection at a distance) tended to be very small and not significant. In other words, summarized preferences seem to have predictive power when participants are considering a situation-selection decision in the abstract, whereas functional preferences seem to have predictive power when participants are selecting into a situation they have had a chance to sample. These results were similar across three analytic approaches (including when measurement error was taken into account with SEM), thus increasing our confidence in their robustness.

Our Reditry paradigm circumvented participants' pre-existing expectations and summarized preferences by requiring them to learn about an unfamiliar trait, thereby creating an ideal context in which to study how summarized preferences form in the first place (Studies 1–3). However, the high experimental control of this paradigm potentially comes at the cost of external validity. To better understand what summarized attribute preferences predict, it is also important to study existing preferences for familiar traits. In addition, to better understand how attribute preferences operate in the realm of romantic attraction, it is also important to move from carefully controlled but narrow stimuli like White CFD faces to more externally valid and diverse stimuli like real-world dating profiles (Ledgerwood et al., 2021). In the next study, we turn to a more externally valid paradigm to better illuminate the consequences of attribute preferences.

Study 4

In Study 4, we set out to test the predictive power of summarized and functional preferences for known, familiar attributes in the real-world context of online dating, where people often have to weigh their interest in different dating websites that may offer access to different pools of partners. We again tested the hypotheses that summarized preferences would primarily predict situation selection at a distance (H2), and that functional preferences would predict situation selection when people can directly sample a situation (H3). As in Study 3, we designed these situation-selection DVs to mimic real-life online dating contexts where people can select websites either at a distance (as when people simply read a description of a website or learn about it from friends) or after sampling the situation (as when people see photographs of other users on the website or sign up for a free trial).

We selected two focal attributes, intelligence and confidence, and measured participants' summarized and functional preferences for the two attributes in potential romantic partners. We used intelligence and confidence as our focal attributes because they can be readily inferred from faces (Oosterhof & Todorov, 2008), allowing us to assess functional preferences following a photograph-evaluation procedure employed in past research on partner preferences (Brumbaugh & Wood, 2013; Eastwick & Smith, 2018; Wood & Brumbaugh, 2009). Using two focal attributes rather than only one also provided us an opportunity to check whether the pattern of results would replicate across different attributes.

Method

The preregistration is publicly available on the Open Science Framework at: https://osf.io/tqfvc/?view_only=48d41b4de11245a78fc64aeb330c15cd.

Participants. Six hundred and eighty-four participants completed the study online through MTurk (see Power Analyses section below for a discussion of our sample size determination). As in Studies 1–2, we limited the age range of participants to 18–35 years old; this time, we included both participants who were primarily attracted to men and those who were primarily attracted to women in a single study. We preregistered four *a priori* exclusion criteria: We would exclude participants who (1) gave an identical rating to all faces presented for measurement of functional preferences, (2) gave an identical rating to all attributes presented for measurement of summarized preferences, (3) provided a response other than male or female to the question asking about their gender (to maintain comparability to other similar studies; e.g., Eastwick & Smith, 2018), and/or (4) failed the attention check presented before the measurement of our dependent variables. In this sample, the number of participants who met each of these exclusion criteria were 9, 3, 5, and 115, respectively. Excluding these participants resulted in a final $N = 555$ (337 women, 218 men; $M_{\text{age}} = 28.9$, $SD = 4.0$; 71.5% White, 12.6% Black/African American, 6.3% Asian or Pacific Islander, 1.4% Native American, 5.9% mixed race or multiracial, 2.2% reported a different race; all self-reported residents in the USA); note that some participants met more than one exclusion criterion.

Procedure. We asked participants to imagine that they were single and looking for a romantic partner. First, they indicated the sex to which they were primarily romantically attracted, which determined the sex of the potential partners presented to each participant throughout the rest of the study. Then, participants completed measures of (a) summarized preferences for intelligence and confidence and (b) functional preferences for intelligence and confidence (order of attributes and order of summarized versus functional measures were each randomized across participants). All participants then completed an attention check.

Next, participants saw the situation selection measures, which were similar to the ones used in Study 3. To assess participants' interest in selecting into situations at a distance, without experiencing or sampling any targets from those situations, we presented a pair of dating websites and described one dating website as designed "for people looking for smart partners." Participants learned that if they joined this website, they would "have access to potential partners who are in the top 30% of intelligence." We described the other dating website as designed "for people looking for self-assured partners." Participants learned that if they joined this website, they would "have access to potential partners who are in the top 30% of confidence." We then measured participants' interest in these two websites (the order in which participants indicated interest for these two websites was randomized).

To assess participants' interest in selecting into situations that they had an opportunity to directly sample, we presented participants with a different pair of dating websites, Website A and Website B. We gave participants the opportunity to sample these websites by showing them an ostensible screenshot of each website, which contained photographs of targets that were particularly high on one of the attributes. Because positive attributes (like intelligence and confidence) tend to be correlated in face impressions (e.g., Stolier et al., 2018), we selected photographs that were high on one attribute but not the other, so that participants' responses to a given website would indicate interest in a situation with higher levels of the attribute in question, rather than interest in a generically positive situation. Thus, the screenshot of Website A consisted of photographs of targets that were high on confidence but low on intelligence, and the screenshot of Website B consisted of photographs of targets that were high on intelligence but low on confidence. The screenshots were presented side by side. We then measured participants' interest in these two websites.

As in Study 3, we randomized the order of the situation-selection dependent variables. Last, participants provided their demographic information.

Materials and measures.

Summarized preference measure. To assess participants' existing summarized preferences for familiar traits, we presented them with a list of 16 traits and they rated the extent to which they desired each attribute in an ideal romantic partner on a 7-point Likert-type scale (from 1 = *not at all* to 7 = *a great deal*; adapted from Joel et al., 2017). Participants' summarized preference for intelligence was calculated as the mean of ratings for *intelligent*, *smart*, and *intellectually sharp* ($\alpha = .89$), and participants' summarized preference for confidence was calculated as the mean of ratings for *confident* and *self-assured* ($\alpha = .79$; see the supplemental materials for the full list of rated attributes and their descriptive statistics).[8]

Functional preference measure. To assess participants' functional preferences for intelligence and confidence, we adapted the same measures used in Studies 1–3 with one key change: To enhance the external validity of our study, we used photographs that we collected from actual dating profiles on a publicly accessible dating website (100 male targets, 100 female

[8] We collected ratings on one additional item related to confidence ("charismatic"). Following our pre-analysis plan, we dropped the item from our calculation of summarized preference for confidence because including this item lowered the internal consistency of scale by more than $\Delta\alpha = .01$. Including the item did not substantively change our results (e.g., no change of levels of significance, and no decline in the fit of our structural equation models; see the supplemental materials for details).

targets) rather than the carefully posed faces from the Chicago Face Database. We collected trait ratings for each target profile in an independent MTurk sample ($N = 132$; see Study S3 in the supplemental materials for details).[9] Our measure of liking for each target was also slightly different simply because the materials were designed by a different researcher: Participants rated the extent to which they experienced romantic desire (rather than "romantic interest") for each target, again on a 9-point Likert-type scale (from 1 = *not at all* to 9 = *a great deal*).[10] Functional preference for an attribute was calculated in the same way as Studies 1–3: Each participant's romantic desire ratings were rescaled to a POMP metric ranging from 0 to 100, such that 0 indicated the scale floor (*not at all*) and 100 indicated the scale ceiling (*a great deal*). Next, the POMP-rescaled ratings were regressed onto the levels of the attribute. Finally, the standardized regression coefficients from the regression models were *r*-to-*z* transformed. Each transformed regression coefficient represents a participant's own functional preference for a given attribute. As would be expected given the higher number of trials in the current study, the reliabilities of functional preferences were higher than in prior studies (αCP = .74, intelligence for male faces; αCP = .71, confidence for male faces; αCP = .73, intelligence for female faces; αCP = .80, confidence for female faces).

Attention check. We again included an attention check to filter out inattentive participants, this time adapted from the standard instructional manipulation check (IMC; Oppenheimer et al., 2009). A paragraph embedded within the study procedure instructed

[9] Just as in real-life online dating contexts, we are agnostic of the "true" level of intelligence and confidence in our targets. Rather, levels of attributes are inferred from faces, and past research suggests that the focal attributes we measured elicit a high level of consensus: In other words, people agree on how intelligent and confident targets look (Oosterhof & Todorov, 2008).

[10] Items assessing "romantic interest," "romantic desire," and "romantic liking" can be viewed as interchangeable. In Study S2, romantic desire was strongly associated with both romantic interest, $\beta_{desire.interest} = .87$, 95% CI [.86, .89], and romantic liking, $\beta_{liking.desire} = .84$, 95% CI [.82, .86], all *p*s < .001 (see the supplemental materials for details).

participants to ignore a question that appeared underneath the paragraph and instead simply confirm that they had read the instructions.

Situation selection at a distance. To assess participants' interest in entering a not-yet-experienced situation with (a) highly intelligent partners or (b) highly confident partners, we adapted the situation selection item from Studies 2–3: Participants indicated how interested they were in the website described as providing access to partners in the top 30% of intelligence, and (in a separate question) how interested they were in the website providing access to partners in the top 30% of confidence on a 9-point Likert-type scale (from 1 = *not at all interested* to 9 = *very interested*).

Situation selection with experience. To assess participants' interest in entering a situation with (a) highly intelligent partners or (b) highly confident partners after having a chance to sample targets from those situations, we presented participants with screenshots of two websites and asked them to indicate which dating website they would choose to join. The first website screenshot contained six photographs of targets that were relatively high on confidence (top 40% of our stimuli set) but middling on intelligence (bottom 40% of our stimuli set), whereas the second website screenshot contained six photographs of targets that were relatively high on intelligence (top 40% of our stimuli set) but middling on confidence (bottom 40% of our stimuli set; see Figure 5).

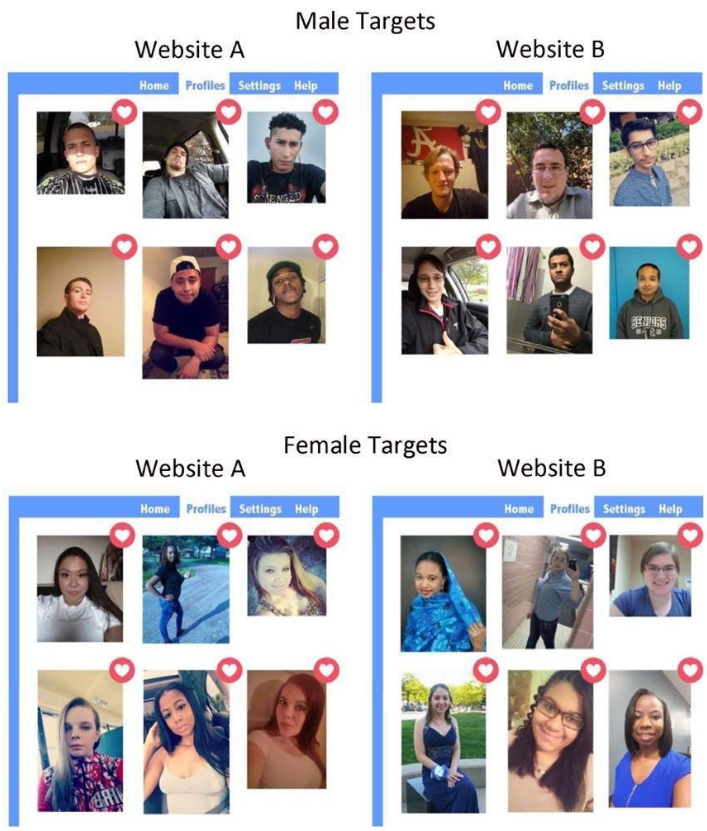

Figure 5. Stimuli used in Study 4 for the dependent measure of situation selection with experience. The screenshot of Website A presented photographs of six targets that had been rated in an independent sample (Study S3 in the supplemental materials) as relatively high on confidence but middling on intelligence, and the screenshot of Website B presented photographs of six targets that had been rated as relatively high on intelligence but middling on confidence. The two websites appeared side by side on the same screen and participants selected their choice by clicking on one of the two screenshots.

Secondary dependent measures. Recall our focal hypotheses: We expected that summarized preferences would predict situation selection at a distance (H2), whereas functional preferences would predict situation selection with experience (H3). To explore the extent to which such results might be driven by the particular format of the primary dependent measures described above, we included two additional, secondary dependent measures after participants read about the websites that would provide access to (a) highly intelligent partners and (b) highly confident partners. First, to examine whether summarized preferences would only predict situation selection when the dependent measure focuses on one situation at a time (i.e., as in our primary *situation selection at a distance* measure), we included a measure that forced a tradeoff between the two situations: Participants indicated how interested they were in one website versus the other on a 9-point bipolar scale (1 = *the website that would only include intelligent partners*, 9 = *the website that would only include confident partners*). Second, to examine whether functional preferences would specifically predict a choice between two experienced situations (i.e., as in our primary *situation selection with experience* measure) or more broadly predict any kind of binary choice, we included a measure that asked participants to choose between the two described websites: Participants indicated which of the two described websites they would choose to join if both websites were available to them at the same price.

Power analyses for determining sample size. We determined our target sample size by running a series of power analyses using Monte Carlo simulations (Muthén & Muthén, 2002; Wang & Rhemtulla, 2021). We powered our study at 80% (with $\alpha = .05$) to detect the three quantities of interest that would be most difficult to detect in our design: (1) the effect of functional preferences for intelligence on choice between experienced websites in our planned structural equation model, controlling for functional preferences for confidence, (2) the effect of functional preferences for confidence on choice between experienced websites in the structural equation model, controlling for functional preferences for intelligence, and (3) level of model misfit in the structural equation model. In power analyses for the first two effects, we used parameter estimates observed in a preliminary study ($N = 332$; $\beta_1 = .13$, $\beta_2 = .18$) to create the population model, from which we generated simulated data. In power analysis for the third effect, we followed the procedure described by MacCallum et al. (1996) by specifying the null hypothesis of close fit as H0: RMSEA = 0.05 and the alternative hypothesis of not-close fit as Ha: RMSEA = 0.10. These simulation-based power analyses showed that the minimum target sample size that would give us at least 80% power to detect all three effects was 535. We anticipated an exclusion rate of at least 15% based on a preliminary study and oversampled to ensure that we would have at least $N = 535$ for analysis. All power analyses were conducted in R using the ‘lavaan’ package (R Core Team, 2018; Rosseel, 2012).

Results

Hypotheses 2 and 3: preregistered analyses. We tested our hypotheses that summarized preferences would predict situation selection at a distance (H2), whereas functional preferences would predict situation selection with experience (H3). As in Study 3, we decided *a priori* to focus on the effect sizes and *p*-values from one focal approach (SEM), while also considering the consistency of the patterns across two alternative analytic approaches (bivariate and multiple regressions).

Our planned focal approach was to use SEM to test the effect of a summarized or functional preference for an attribute on a dependent variable, while controlling for the same type of preference for the other attribute (e.g., testing the effect of functional preference for confidence on a dependent variable, controlling for functional preference for intelligence; see Figure 6 for conceptual diagrams). In each SEM analysis, the dependent variable was simultaneously regressed on two predictors that were modelled as latent factors. Latent factors of summarized preferences were measured with each item as an indicator (i.e., *intelligent*, *smart*, and *intellectually sharp* for intelligence, and *confident* and *self-assured* for confidence). Latent factors of functional preferences were measured by randomly dividing the 100 target stimuli into four parcels, then calculating participants’ functional preferences from each parcel as an indicator (following a random parceling approach; Little et al., 2002). Because the same parcels were used to calculate functional preferences for both intelligence and confidence, we allowed residual covariances of matching parcels (e.g., functional preferences for intelligence from parcel 1 and functional preferences for confidence from parcel 1) to be freely estimated.

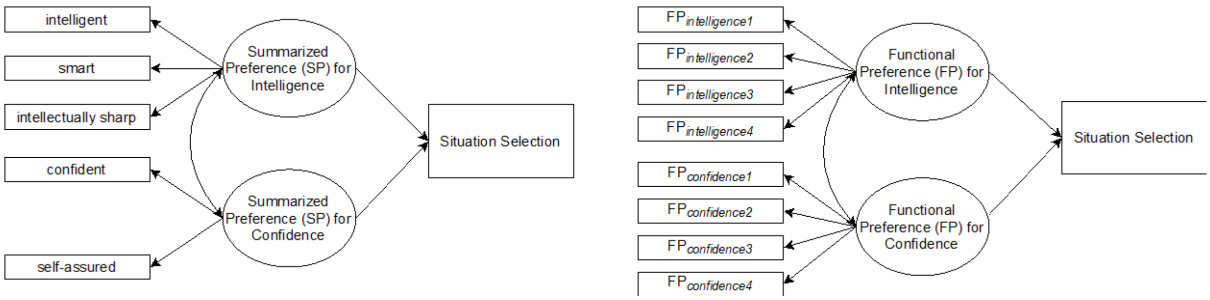

Figure 6. Conceptual diagrams of the planned structural equation models testing H2 and H3. Each situation selection dependent variable was simultaneously regressed onto summarized preferences (left panel) or functional preferences (right panel). For visual simplicity, residual (co)variances are not shown.

We further planned to interpret the results of our focal approach in the context of two other analytic approaches: bivariate and multiple regressions, which provide estimates that are conceptually akin to raw and semipartial correlations, respectively. For the bivariate regression approach, we planned to model the direct effects of summarized and functional preferences by regressing dependent variables on preference variables (as composite scores) and examining the effect size estimates as regression coefficients of the predictors. For the multiple regression approach, we planned to model the partial effects of summarized and functional preferences by conducting multiple regressions in which dependent variables were simultaneously regressed on the same type of preferences for the two attributes and examining the effect size estimates provided by the partial regression coefficients of the predictors.

Primary situation-selection dependent measures. Our main analyses tested the extent to which summarized preferences and functional preferences each predicted situation selection at a distance (H2) and situation selection with experience (H3; Table 3). All models fit the data reasonably well, χ^2s = 1.23–265.30, CFIs = 0.90–1.00, TLIs = 0.84–1.00, RMSEAs = 0.02–0.14 (see supplement for details).

Table 3.

Summarized and Functional Preferences Predicting Primary Dependent Variables in Study 4.

Analytic Approaches	Predictor Type	Dependent Variables	Attributes: Intelligence					Confidence				
			b (*SE*)	*p*	*β*	*OR*	*r* [95%CI]	*b* (*SE*)	*p*	*β*	*OR*	*r* [95%CI]
Structural Equation Models	SP	SS at a distance	0.90 (0.13)	< .001	0.39	-	.32 [.24, .41]	0.86 (0.14)	< .001	0.38	-	.31 [.22, .40]
	FP	SS at a distance	0.40 (0.18)	.026	0.17	-	.11 [.01, .21]	0.24 (0.18)	.174	0.10	-	.07 [-.03, .17]
	SP	SS with experience	0.44 (0.13)	< .001	-	1.55	.12 [.05, .19]	0.54 (0.13)	< .001	-	1.71	.15 [.08, .21]
	FP	SS with experience	1.06 (0.13)	< .001	-	2.87	.28 [.22, .34]	1.44 (0.13)	< .001	-	4.21	.37 [.31, .42]
Bivariate Regression	SP	SS at a distance	0.73 (0.09)	< .001	0.33	-	.33 [.15, .50]	0.59 (0.08)	< .001	0.29	-	.29 [.13, .45]
	FP	SS at a distance	1.06 (0.49)	.031	0.09	-	.09 [.008, .17]	0.39 (0.43)	.366	0.04	-	.04 [-.04, .12]
	SP	SS with experience	0.13 (0.10)	.192	-	1.13	.03 [-.02, .09]	0.23 (0.08)	.006	-	1.25	.06 [.02, .11]
	FP	SS with experience	0.46 (0.48)	.339	-	1.59	.13 [-.13, .36]	2.95 (0.46)	< .001	-	19.08	.63 [.50, .73]
Multiple Regression	SP	SS at a distance	0.75 (0.10)	< .001	0.34	-	.30 [.12, .47]	0.62 (0.09)	< .001	0.31	-	.27 [.11, .43]
	FP	SS at a distance	1.36 (0.66)	.039	0.12	-	.09 [.004, .17]	0.74 (0.57)	.193	0.07	-	.06 [-.03, .14]
	SP	SS with experience	0.32 (0.11)	.004	-	1.38	.09 [.03, .15]	0.36 (0.10)	< .001	-	1.44	.10 [.05, .15]
	FP	SS with experience	5.48 (0.78)	< .001	-	239.86	.83 [.74, .88]	6.41 (0.72)	< .001	-	605.52	.87 [.81, .91]

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection, OR = odds ratio. Unstandardized regression coefficients (*b*) for situation selection with experience are logit coefficients.

Hypothesis 2 again received support: Summarized preferences for both intelligence and confidence significantly predicted situation selection at a distance across all three approaches. Functional preferences barely predicted situation selection at a distance; effect sizes for both attributes were small and only sporadically significant. Hypothesis 3 received support as well, as functional preferences for both intelligence and confidence predicted situation selection with experience with moderate effect sizes. The effects of summarized preferences on situation selection with experience tended to be much weaker. The double dissociation pattern is most evident in the focal SEM approach, but the pattern with the other two approaches is similar.[11]

Secondary situation-selection dependent measures. To examine whether the findings for H2 could have been driven by incidental differences in the format of our primary dependent measures, we conducted planned analyses on our secondary dependent measures using the same analytic approaches. Specifically, we tested whether summarized preferences would still strongly predict situation selection at a distance if we forced a tradeoff between one website versus another, and whether using a binary choice version of this "at a distance" measure affected the predictive power of functional preferences. Results showed similar patterns of dissociation on the secondary dependent measures, where summarized preferences predicted situation selection at a distance more strongly than functional preferences, regardless of the format of those dependent measures. These results suggest that the support we observed for H2 on the primary dependent measures was not a measurement artifact (see the supplemental materials for details).

Hypotheses 2 and 3: exploring a full model of double dissociation. In addition to the preregistered analyses, we explored the full pattern of double dissociation by fitting a model in

[11] Note that, unlike Study 3, we cannot test the difference between the functional versus summarized preference effect sizes because the two preferences were not entered simultaneously per our analysis plan. We present a test of this idea in the section "Hypotheses 3 and 4: exploring a full model of double dissociation" below. This analysis was preregistered in Study 3 because we conducted Study 3 after we conducted Study 4.

which the primary dependent variables were simultaneously regressed on all attribute preferences we measured (i.e., summarized and functional preferences for both attributes; see Figure 7). Each attribute preference predictor was modelled as a latent predictor in the same way as our planned structural equation models. This model allowed us to further isolate the unique predictive validity of each attribute preference variable (e.g., summarized preference for intelligence), controlling for the effects of both the same type of attribute preference for the other attribute (e.g., summarized preference for confidence) and the other type of attribute preference for the same attribute (e.g., functional preference for intelligence).

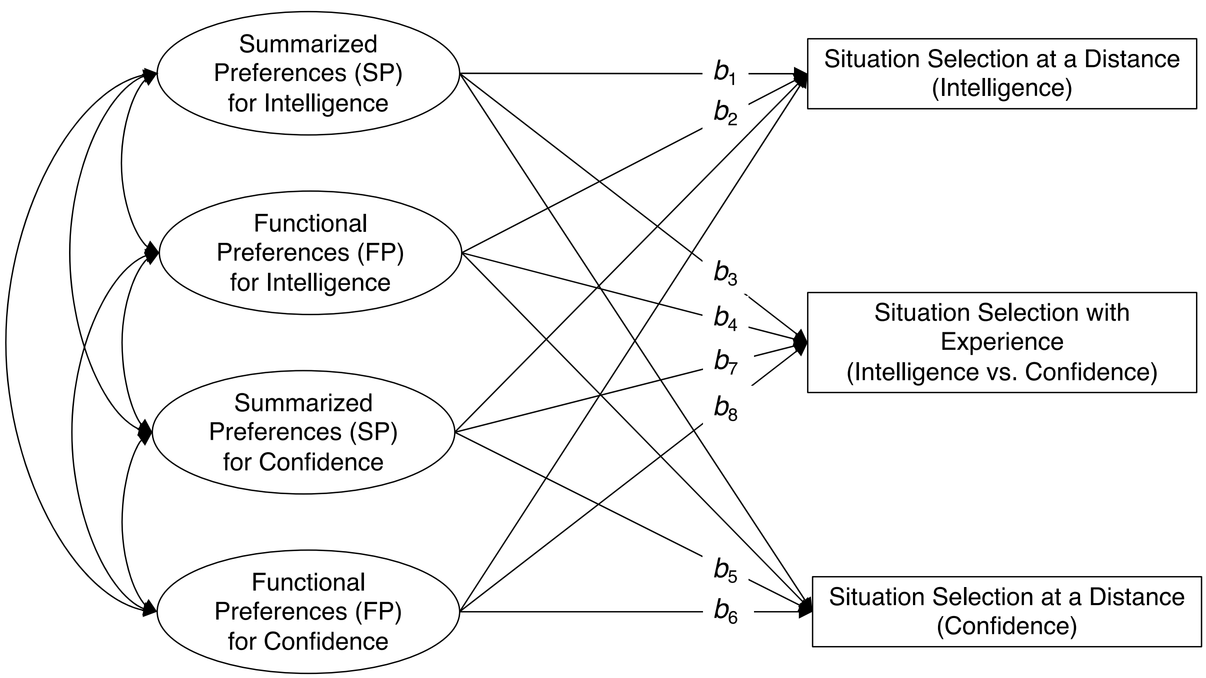

Figure 7. Diagram of the full model of double dissociation in which primary dependent variables were regressed on all attribute preferences as latent predictors. Key parameters showing the double dissociation pattern are denoted b_1–b_8 and reported in Table 4. For visual simplicity, residual (co)variances and measurement model of the latent predictors are not shown.

This model provides a good fit of the data, $\chi^2(83) = 178.16$, $p < .001$, CFI = 0.98, TLI = 0.97, RMSEA = 0.05. Correlations among key variables are reported in Table A2 (Appendix), and key parameters testing the double dissociation are reported in Table 4. We observed a full double dissociation between summarized and functional preferences predicting situation selection dependent variables. Summarized preferences predicted situation selection at a distance (H2), and this effect was stronger than the effect for functional preferences (intelligence: $b_1 > b_2$, $\Delta\chi^2(1) = 10.26$, $p = .001$; confidence: $b_5 > b_6$, $\Delta\chi^2(1) = 17.77$, $p < .001$). In contrast, functional preferences predicted situation selection with experience (H3), and this effect was stronger than the effect for summarized preferences (intelligence: $b_4 > b_3$, $\Delta\chi^2(1) = 5.28$, $p = .022$; confidence: $b_8 > b_7$, $\Delta\chi^2(1) = 20.46$, $p < .001$).

Table 4.

Key Parameters in the Full Model of Double Dissociation in Study 4.

Predictor Type	Dependent Variables	Attributes									
		Intelligence					Confidence				
		Parameter	*b* (*SE*)	*p*	β [95%CI]	*OR* [95%CI]	Parameter	*b* (*SE*)	*p*	β [95%CI]	*OR* [95%CI]
SP	SS at a distance	b_1	0.85 (0.12)	< .001	0.37 [0.28, 0.46]	-	b_5	0.25 (0.13)	< .001	0.39 [0.29, 0.49]	-
FP	SS at a distance	b_2	0.15 (0.15)	.323	0.06 [-0.06, 0.19]	-	b_6	0.06 (0.15)	.769	0.02 [-0.11, 0.14]	-
SP	SS with experience	b_3	0.37 (0.14)	.006	-	1.45 [1.11, 1.90]	b_7	0.35 (0.14)	.011	-	1.42 [1.08, 1.85]
FP	SS with experience	b_4	0.92 (0.14)	< .001	-	2.51 [1.91, 3.32]	b_8	1.37 (0.13)	< .001	-	3.94 [3.05, 5.08]

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection, OR = odds ratio. Unstandardized regression coefficients (*b*) for situation selection with experience are logit coefficients.

Discussion

The results of Study 4 suggested that although summarized and functional preferences may be only weakly related to each other, both have predictive power. First, we observed a double dissociation between summarized and functional preferences, such that summarized preferences strongly predicted situation selection at a distance (as when people read a description of a website; H2), but functional preferences did so only weakly. In contrast, functional preferences strongly predicted situation selection with experience (as when people see photographs of other website users; H3), but summarized preferences did so only weakly. These results emerged across both of our focal attributes and were similar across a variety of analytic approaches (including when measurement error was taken into account with SEM), thus increasing our confidence in their robustness and generalizability. Moreover, the results from our secondary analyses did not support the possibility that the results for Hypothesis 2 was driven by the particular features of the format of our primary dependent measures: Summarized preferences strongly predicted situation selection at a distance (H2) regardless of whether that dependent variable was measured as interest in a single website (measure i), interest in one website versus the other (measure iii), or a choice between two websites (measure iv). This robust pattern provided strong support for our *a priori* theoretical prediction that people would rely on their summarized preferences to make decisions about situations that they have not yet entered or sampled (see Ledgerwood et al., 2018, Model 3).

One distinction between summarized and functional preferences in the current study is worth noting: The summarized preference measure (and the situation selection at a distance DV) presumably captures participants' beliefs about their evaluative responses to targets who actually behave intelligently/confidently in real life. But the functional preference measure (and the situation selection with experience DV) captures how participants reacted to targets who appear intelligent/confident. It seems plausible, then, that the functional preference measure is more likely to differ across contexts (e.g., viewing photos vs. speed-dating) for a given participant. Although this line of reasoning is consistent with our suggestion that summarized and functional preferences differ in their level of abstraction and context-specificity (Ledgerwood et al., 2018; Trope et al., 2021), the "appearance vs. actual" trait distinction could be contributing to the double dissociation pattern we observed in this study. However, this issue did not apply to Study 3, where all information about summarized and functional preferences for Reditry had been acquired by looking at photographs. Thus, the appearance vs. actual trait distinction cannot explain the consistent support for H2 and H3 that we see across our full set of studies.

General Discussion

People can summarize their attribute preferences (e.g., "I like intelligence in a partner;" "I value loyalty in a friend") and communicate these preferences to others. But where do these summarized preferences come from, and what do they predict? In this research, we set out to investigate the possibility that summarized preferences have some unique antecedents and consequences that distinguish them from functional preferences (e.g., the extent to which intelligence predicts positivity toward a romantic partner).

First, summarized preference formation was sensitive to incidental features in the learning context that were independent of functional preferences. Specifically, summarized preferences were biased by the likeability of a pool of encountered targets (H1). When participants were asked to form summarized preferences for an unfamiliar attribute, they reported that they liked Reditry more when the pool of faces that they encountered during the learning task was more (vs. less) likeable, functional preferences notwithstanding. This effect parallels the outcome density bias in the covariation detection literature: People think a predictor (in this case, Reditry) is more important when the outcome to be predicted (in this case, liking) is common rather than rare. These findings complement earlier work suggesting that another covariation detection bias—the cue-density bias—also affects the formation of summarized preferences in a mating context (Eastwick et al., 2019). Together, these studies suggest that summarized preferences are informed not only by a person's experienced functional preferences for an attribute, but also by other independent features of the learning context.

Second, we examined the downstream consequences of summarized as well as functional preferences. We found that summarized preferences predicted situation selection at a distance, such as the extent to which participants wanted to join a website featuring partners high in Reditry, high in intelligence, or high in confidence (H2). Intriguingly, functional preferences did not predict this outcome especially well. Instead, functional preferences predicted situation selection with experience (i.e., participants' website selection when they saw example profiles of partners high in Reditry, high in intelligence, or high in confidence; H3). We found evidence of this double dissociation for both an unfamiliar attribute in a set of well controlled, standardized photographs (Study 3), as well as for two familiar attributes in a set of externally valid, naturalistic photographs (Study 4). Taken together, the unique antecedents and consequences of summarized preferences lend support to the proposal that summarized and functional preferences are distinct types of evaluative constructs that may serve different psychological purposes.

Studies 1-3 (and H1) centered on the formation of attitudes towards attributes, and so we used the unfamiliar term "Reditry" to circumvent participants' pre-existing associations with the concept of babyfacedness. Indeed, only 3 out of 831 participants in Studies 1-3 mentioned anything related to babyfacedness or youthfulness across 4 separate comment boxes probing for thoughts about the study. This design feature enabled us to study how attitudes toward attributes form in the first place, as people first experience their liking for targets with varying levels of an attribute. Our studies are similar in this regard to the longstanding literature on attitude formation toward novel stimuli, which has shown that people can readily evaluate a new "thing" (in this case, Reditry) regardless of whether they can clearly articulate what the thing is (e.g., Duckworth et al., 2002; Fazio et al., 2015). At the same time, studying the very beginning of the attitude formation process—when participants have had relatively little experience with an attribute or object—necessarily means that a set of findings may be limited to this early phase, and might change when participants garner more experience. The fact that we observed similar patterns of results across Study 3 (unfamiliar attribute/little experience) and Study 4 (familiar attributes/extensive experience) gives us some confidence that functional and summarized preferences start out as distinguishable and continue to be distinguishable even as people gain considerable experience with an attribute.

Implications for Understanding Human Evaluation

Different traditions in the study of attribute preferences. Researchers across multiple disciplines are interested in understanding how humans evaluate attributes. For example, large literatures in the fields of family studies, evolutionary psychology, and close relationships have investigated people's summarized preferences for attributes in a romantic partner (e.g., Buss, 1989; Christensen, 1947; Fletcher et al., 1999; Hill, 1945). Likewise, researchers have examined summarized preferences for attributes of friends, leaders, and teachers (Delaney et al., 2010; Goodwin & Tang, 1991; Pew Research Center Survey, 2015). Meanwhile, researchers who study consumer preferences assess functional preferences for attributes in products (e.g., Delgado & Guinard, 2011; Silayoi & Speece, 2007), researchers who study organizational behavior examine functional preferences for attributes of job candidates and organizations (Heilman & Saruwatari, 1979; Turban & Keon, 1993), and political scientists investigate functional preferences for attributes of election candidates (Carnes & Lupu, 2016).

Across these literatures, researchers tend to assess either summarized preferences or functional preferences following the prevailing measurement tradition in their field. Yet our studies suggest that the distinction between summarized and functional preferences is deeper than a trivial difference in measurement traditions, and researchers should think carefully about which construct they are actually interested in understanding conceptually, and/or what type of outcome they are trying to predict (see also the discussion of measurement correspondence below). Specifically, summarized preferences might be particularly useful when researchers are interested in what people think they like, or contexts in which ideas of liking can be consequential, such as when people introspect about their liking, and when people communicate their liking with each other. In contrast, functional preferences might be particularly useful when researchers are interested in people's in-the-moment experience of liking, or contexts in which experiences of liking are consequential. When it comes to prediction, researchers may wish to prioritize the assessment of summarized preferences when their goal is to predict decisions at a distance (e.g., whether to visit a destination based on a description in a guidebook; whether to date someone based on an online dating profile). In contrast, researchers may wish to prioritize the assessment of functional preferences when their goal is to predict decisions made with direct experience (e.g., whether to visit a destination for the second time; whether to date someone after meeting them in person; see also Eastwick et al., 2011; Huang et al., 2020).

The large literature on human mate preferences is an interesting case in point. Conceptually speaking, functional preferences are the mate preferences that would have had clearer relevance to ancestral humans; that is, natural selection should have shaped the human mind to positively evaluate real-life mates depending on the extent to which those mates possess certain attributes (Conroy-Beam et al., 2016). Yet summarized preferences—people's *ideas* about the attributes that appeal to them—are studied far more commonly than functional preferences in the human mate preferences literature (e.g., Buss, 1989; Fletcher et al., 1999), and authors routinely use the word "preference" interchangeably to describe both functional and summarized preferences (e.g., Gerlach et al., 2019; cf. Eastwick et al., 2019). The current findings suggest that researchers studying human mate preferences should make a careful and deliberate choice for any given study about whether to assess functional preferences, summarized preferences, or both. For example, if researchers intend to study a mate selection process that could conceivably be a facsimile of an ancestral selection process, functional preferences are likely the appropriate choice, assuming that researchers have access to enough stimuli to achieve a reliable αCP (Sherman & Wood, 2014; Wood & Brumbaugh, 2009). But researchers also might wish to study the (perhaps uniquely) human ability to draw upon abstract ideas about preferences to guide decisions at a distance (e.g., which outgroup members to meet, which families are suitable for arranging marriages); in these cases, summarized preferences might be especially likely to inform such decisions.

Ideas about liking versus experiences of liking. More broadly, it may be useful to distinguish between people's abstract *ideas* about liking and their concrete *experiences* of liking. In this paper, we have considered this distinction as it applies to attribute preferences, but a similar distinction may be fruitfully applied to attitudes toward objects (i.e., liking for a person, place, or thing; see Ledgerwood et al., 2020). For example, people can have abstract ideas about their liking for broad social categories (e.g., "I like my college instructors") as well as concrete evaluations of specific encountered exemplars (e.g., "I like this particular college instructor"; Sears, 1983). Drawing a parallel to the present findings generates the prediction that abstract evaluations of categories would better predict situation selection at a distance (e.g., whether to take a job described as involving interactions with college students), whereas concrete evaluations of exemplars would better predict situation selection with experience (e.g., whether to take a job after meeting some specific college students in person). A similar distinction exists in the study of attitudinal properties, which differentiates between people's ideas about the affective versus cognitive cause of their attitudes and the actual affective versus cognitive cause of their attitudes (See et al., 2008, 2011). Our work generates the prediction that beliefs about attitudinal properties will have greater relevance to situation selection at a distance, whereas actual attitudinal structure will have greater relevance to situation selection with experience.

The current findings also suggest intriguing hypotheses regarding the consequences of preference-guided situation selection for future research to investigate. To the extent that ideas and experiences of liking diverge, people might select into situations at a distance based on their ideas about liking, but not actually experience more liking once they are in the selected situation (vs. alternative situations). This phenomenon would have implications for myriad real-life contexts. From exclusive dating websites to buying a house, people frequently select themselves into situations and limit the sets of stimuli they subsequently experience based on advertisements, reviews, conversations, and other socially acquired knowledge. People may go to great lengths to enter a certain situation, raise their expectations accordingly, but then not feel as much liking as they anticipated once they have the experience. Future research should examine the possibility that discrepancies between people's ideas about their likes and their actual experiences of liking could create a "cycle of disappointment" along these lines.

Expanding our understanding of measurement correspondence. The present work follows the footsteps of Ajzen and Fishbein's (1977, 2005) classic work on the compatibility principle, which suggests that an attitude will better predict a behavioral criterion when the two measures correspond in terms of their generality or specificity. A recent resurgence of attention to this issue has led to new insights and predictions for the study of social influence and implicit bias, as well as attribute preferences (Gawronski, 2019; Irving & Smith, 2020; Ledgerwood et al., 2018; Ledgerwood & Trope, 2010). In a similar vein, our current findings highlight the importance of considering correspondence between measures of attribute preferences and measures of downstream consequences. We examined situation selection DVs with real-world relevance, and there is indeed conceptual similarity between (a) the measurement of summarized preferences and situation selection at a distance, as well as (b) the measurement of functional preferences and situational selection with experience (see also Lievens & Sackett, 2017; Miller et al., 2019).

At the same time, it is important to consider the ways in which the present research expands beyond pure measurement correspondence. Notably, Ajzen and Fishbein (1977, 2005) did not consider the compatibility principle in the context of attitudes toward attributes (see Ledgerwood et al., 2018, for a full discussion). Indeed, the closest analog to the summarized/functional distinction in their work was a distinction between two different measures of *general* attitudes that they treated as interchangeable (Ajzen & Fishbein, 1977): namely, (1) an overall evaluation of a general attitude object (e.g., a person's favorability toward maintaining good physical health) and (2) the average of a series of evaluations of specific attitude objects (e.g., a person's average favorability toward eating more vegetables, avoiding junk food, exercising daily, and getting regular checkups). Because summarized and functional preferences would have been treated as two forms of general attitudes, a prediction from Ajzen and Fishbein's conceptualization would be that summarized and functional preferences should predict outcomes equally. In contrast, we posit that summarized and functional preferences are distinct: Summarized preferences are abstract evaluations of attributes as concepts, whereas functional preferences are concrete evaluations of attributes as experiences. Drawing from work on construal level fit (Fujita et al., 2008; Lee et al., 2010), we predicted and found summarized preferences strongly predicted situation selection at a distance, whereas functional preferences strongly predicted situation selection with experience. These findings, as part of a double dissociation, is (broadly speaking) a form of correspondence, but it is not derivable from the Fishbein and Ajzen correspondence principle, which predated construal level theory.

Perhaps most importantly, the existence of divergent measurement traditions for assessing attribute preferences suggests that the issue of correspondence has yet to receive sufficient attention in these literatures. By demonstrating the distinct predictive validity of summarized and functional attribute preferences, our work highlights the importance of considering measurement compatibility for future research on attribute preferences in human mating, consumer preferences, organizational behavior, and beyond.

Strengths and Limitations

Drawing from multiple literatures on attribute preferences, we tested novel hypotheses on the distinct antecedents and consequences of summarized preferences. We tested these new hypotheses using well-powered studies, preregistered analyses, and both experimental and correlational designs, which together give us confidence that our results are likely robust. In addition, the online dating context used in Study 4 had the advantage of mimicking real-life situation selection and allowing us to manipulate how the situations were presented.

However, further research is needed to test the extent to which our findings will generalize beyond contexts in which people evaluate photographs and participate in online dating. On the one hand, consider that summarized and functional preferences of attributes correlate more strongly in less complex, nonsocial objects (e.g., juices; Alcser et al., 2021). Therefore, the double dissociation in downstream predictive consequences might weaken or disappear when people select into situations involving nonsocial objects. On the other hand, summarized and functional preferences are effectively uncorrelated for attributes perceived via naturalistic face-to-face interactions (Ledgerwood et al., 2018; Eastwick et al., 2021; Sparks et al., 2020). It would be useful for future research to examine these contexts, too. The generalizability of our findings is also constrained by the limited diversity of our stimuli and participants: Most of our participants were White, and we used all White faces in Studies 1–3 (to partially remedy this limitation, the stimuli in Study 4 drew from a racially diverse population). Therefore, our results might not generalize beyond the specific national (i.e., American) and cultural contexts within which this research was conducted (Ledgerwood et al., 2021). Future research could fruitfully examine the generalizability of our results by using larger, more diverse pools of stimuli and participants (e.g., cross-cultural investigations).

Future research can also further clarify the relation between functional and summarized preferences. For example, functional-summarized preference correlations may be relatively weak because functional preferences are not accessible and/or not diagnostic when people report their summarized preferences (Feldman & Lynch, 1988). It might be possible to gather evidence for these mechanisms by incorporating existing manipulations of accessibility (e.g., filler tasks; Ahluwalia & Gurhan-Canli, 2000) or diagnosticity (e.g., instructions that using a certain information is "good"; Zhang & Khare, 2009) and observing whether the functional–summarized preference correlation shifts accordingly. It is also possible (perhaps especially for the unfamiliar attribute Reditry) that participants had a vague or idiosyncratic understanding of what features connote the trait. Although this issue surely applies to real-life attributes, too (i.e., not all people will precisely agree on the behaviors that connote intelligence or confidence), perhaps functional–summarized correspondence will be higher in cases where people have high consensus about the meaning of and behaviors that connote a particular trait. Also, for all three attributes in these studies (i.e., Reditry, confidence, intelligence), the functional preference was calculated using the consensus score provided by a separate set of raters; this is not the only way to measure the attribute in a functional-preference calculation. It is plausible that correspondence between functional and summarized preferences will be higher in cases where the participant provides the attribute rating, as this measurement approach likely reflects all the information (both consensual and idiosyncratic) that the participant could be using to derive an evaluative judgment (Eastwick, Neff, et al., 2014).

Finally, it is important to note that the αCP reliabilities were quite low in studies where we had modest (e.g., 24-40) rather than large (e.g., 100) numbers of trials. Scholars who are interested in studying experiences of liking will want to find novel and creative ways of developing functional preference measures that incorporate as many trials as possible, especially if they want to use these preferences to predict other measured variables. One of the next great challenges will be the development of such a measure that can be used with real people, so that researchers can study functional preferences for attributes that are typically experienced in live interactions rather than inferred from a face.

Conclusions

The current research provides an important first step in understanding the predictive power of summarized and functional preferences and begins to delineate when and how summarized preferences may be useful. Going forward, we believe the interdisciplinary study of attribute preferences will greatly benefit from researchers carefully considering which preference construct they are interested in understanding and which outcomes they are trying to predict.

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Appendix

Table A1.

Correlations among key variables in Study 3.

Variable	1	2	3
1. SP for Reditry			
2. FP for Reditry	.11**		
3. SS at a distance	.40***	.11*	
4. SS with experience	.05	.14***	.05

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection. *$p < .05$, **$p < .01$, ***$p < .001$.

Table A2.

Correlations among key variables in Study 4.

Variable	1	2	3	4	5	6
1. SP for intelligence						
2. SP for confidence	.47**					
3. FP for intelligence	.18**	-.04				
4. FP for confidence	.16**	.08*	.66**			
5. SS at a distance (intelligence)	.33**	.13**	.09*	.04		
6. SS at a distance (confidence)	.11**	.29**	-.00	.04	.52**	
7. SS with experience (for confidence vs. intelligence)	-.06	.12**	-.04	.29**	-.06	.09*

Note. SP = summarized preferences, FP = functional preferences, SS = situation selection. *$p < .05$, **$p < .01$, ***$p < .001$.