Differentiation in social perception:

Why later-encountered individuals are described more negatively

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Abstract

According to the cognitive-ecological model of social perception, biases towards individuals can arise as by-products of cognitive principles that interact with the information ecology. The present work tested whether negatively biased person descriptions occur as by-products of cognitive differentiation. Later-encountered persons are described by their distinct attributes that differentiate them from earlier-encountered persons. Because distinct attributes tend to be negative, serial person descriptions should become increasingly negative. We found our predictions confirmed in six studies. In Study 1, descriptions of representatively sampled persons became increasingly distinct and negative with increasing serial positions of the target person. Study 2 eliminated this pattern of results by instructing perceivers to assimilate rather than differentiate a series of targets. Study 3 generalized the pattern from one-word descriptions of still photos of targets to multi-sentence descriptions of videos of targets. In line with the cognitive-ecological model, Studies 4-5b found that the relation between serial position and negativity was amplified among targets with similar positive attributes, zero among targets with distinct positive or negative attributes, and reversed among similar negative targets. Study 6 returned to representatively sampled targets and generalized the serial position-negativity effect from descriptions of the targets to overall evaluations of them. In sum, the present research provides strong evidence for the explanatory power of the cognitive-ecological model of social perception. We discuss theoretical and practical implications. It may pay off to appear early in an evaluation sequence.

Keywords: person perception; serial targets; distinctiveness; negativity

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A central question in social psychology is how people come to like specific individuals and why they dislike others (Abele et al., 2021). The most intuitive answer is provided by motivational accounts that assume people simply like those individuals from whom they can personally profit. This may include individuals with many resources who are smart, similar to the self, and helpful, or members of one's in-group (Koch, Dorrough, et al., 2020; Koch, Imhoff, et al., 2020). A different, complementary perspective on person perception and the formation of biases is provided by the cognitive-ecological model (Alves et al., 2018; Unkelbach et al., 2019). Biases in social perception may arise as innocent by-products of basic principles of information processing on the one hand, and the structure of the external information ecology on the other hand. The present work applies the cognitive-ecological model to person descriptions and tests whether negatively biased person descriptions arise from cognitive differentiation in a social environment where distinct attributes tend to be negative.

Suppose you serially encounter several individuals at your workplace, at a bar, or in a dating app, and you want to describe them to your friend. You would expect to describe individuals with likable attributes more positively than individuals with unlikable attributes. This assumes that your impressions of sequentially encountered individuals are independent. This, however, is an unlikely scenario according to the cognitive principle of differentiation (e.g., Alves et al., 2020; Florack et al., 2021). When people sequentially encounter stimuli, they tend to prioritize distinct attributes that differentiate a given stimulus from earlier-encountered stimuli (Alves et al., 2018; 2020; Bruine de Bruin & Keren, 2003; Houston et al., 1989; Houston &

Sherman, 1995; Hodges, 1997). This priority operates at different levels of cognition, and Kruschke (2001; 2003) located it at the level of attention, arguing that people flexibly shift their attention to distinct, non-redundant cues. The differentiation principle implies that serial person descriptions become increasingly negative because distinct attributes tend to be negative in the external information ecology while redundant attributes tend to be positive. In other words, while you would describe the first few Tinder profile pictures you encounter rather positively, your descriptions should become increasingly negative as you swipe through the ecology of potential dating partners. Before presenting data from six experiments that tested our predictions, we discuss the cognitive part of the cognitive-ecological model, which argues that person descriptions should follow the differentiation principle. We then delineate the ecological part, which argues that negative person attributes are overrepresented among distinct attributes.

Cognitive Differentiation

Albeit our cognitive apparatus is highly complex, it is governed by several basic principles of information processing. Examples are the range-frequency compromise in category formation (Parducci, 1965), regression in learning (e.g., Furby, 1973; Fiedler & Unkelbach, 2014), or the Weber-Fechner law in psychophysics (Fechner, 1966). Another basic information processing principle is differentiation (e.g., Alves et al., 2018; 2020; 2022), which describes our cognitive system’s tendency to prioritize distinct over redundant information. This principle appears in cognitive and social psychology under various terms. In classical conditioning, cue competition effects such as blocking (Kamin, 1968) and highlighting (Kruschke, 2003) follow the differentiation principle, summarized by the Rescorla-Wagner model (1972). In the impression formation and choice formation domain, the principle is known as cancellation-and-focus effects (Houston et al., 1989). In causal attribution, differentiation has been called the law of uncommon effects (Jones & Davis, 1965). In person perception, the principle is sometimes expressed as a priority given to extreme, informative, or diagnostic information (e.g., Bassok & Trope, 1984; Fiske, 1980; Reeder & Brewer, 1979). Another example is the classic finding that people overestimate the frequency of rare and salient co-occurrences of attributes or events (Hamilton & Gifford, 1976). Research in these domains has found that distinct relative to redundant attributes have a learning advantage (e.g., Rescorla & Wagner, 1972), are overrepresented in memory (Alves et al., 2020), and more strongly drive evaluations and choice formation (e.g., Alves, 2018; Alves et al., 2020; Bruine de Bruin & Keren, 2003; Hodges, 1997; Houston et al., 1989; Houston & Sherman, 1995).

Crucially, the differentiation principle implies that information processing is sensitive to the serial order in which stimuli are encountered. For example, when people learn about the attributes of groups, brands, or consumer products, these will determine the perceptual background against which any novel groups, brands, or products are contrasted. Shared attributes of a novel object remain in the background and the cognitive system focuses on the novel object's distinct attributes, which then dominate preferences, attitudes, and memory content (e.g., Alves et al. 2018; Alves et al., 2020; Bruine de Bruin & Keren, 2003; Hodges, 1997; Houston et al., 1989; Houston & Sherman, 1995; Sherman et al., 2009).

A domain in which the differentiation principle has not been applied is communication, specifically, person descriptions. We predict that a person's distinct attributes are more likely to be described than a person's rather common attributes. Suppose you wanted to describe a new work colleague to your friend. If you are working among engineers, you would probably not refer to the new colleague as "the engineer" because this is a redundant feature. Instead, you will probably search for rather distinct attributes such as that the new colleague is only 4.9 feet tall, or that he has a large scar on his face. The point is that person descriptions should avoid redundancy and instead refer to individuating attributes that differentiate a person from the prototype. This reasoning is well in line with Grice's (1975) conversational maxims, according to which communication is effective if as much information as required is provided but redundancy is avoided. Thus, if people describe a person they can be expected to rely on distinct attributes, whereas redundant ones will be neglected (Alves et al., 2022; Engelhardt et al., 2006).

If the differentiation principle also applies to person descriptions, the serial position in which a person is encountered and described should matter. In serial encounters, the redundancy/distinctiveness of certain attributes is relative and determined over time as more and more persons are encountered. Hence, we can expect that how person Z is described will be influenced by how previously encountered persons X and Y were described. For example, if the firstly encountered person on a dating app is bald, this attribute may be considered an informative description of that person. Yet, once you discover that most of the male persons in this dating app are bald, you will likely divert to other, more distinct person descriptions.

In sum, we predict that the differentiation principle also applies to person descriptions, implying that person descriptions of serially encountered individuals will depend on one another. Over time, they will shift towards attributes that differentiate novel individuals from previously encountered ones. Crucially, we also hypothesize that this will result in more negative person descriptions for later-encountered individuals because distinct person attributes tend to be negative for the two reasons we introduce below.

Why Distinct Attributes Are Negative

While cognitive principles refer to internal psychological processes, the evaluative information ecology (EvIE; Unkelbach et al., 2019; 2020; 2021) is a concept that refers to the external environment. More specifically, it refers to the structure and distribution of information with positive or negative implications. In the social domain, it refers to positive and negative attributes that individuals or groups may possess. Importantly, positive and negative attributes are not symmetrically distributed in the environment, but previous research has identified two fundamental asymmetries.

First, positive attributes occur more frequently than negative attributes, meaning that most people display mostly positive attributes most of the time (e.g., Alves et al., 2017a). Norms, rules, and feedback reward and cultivate positive attributes and, at the same time, punish and eradicate negative attributes (Denrell, 2005; Thorndike, 1898). Consistent with this frequency asymmetry that EvIE (Unkelbach et al., 2019; 2020) assumes, people more often describe others with positive than negative attributes (Ric et al., 2013) and tend to evaluate them positively (Imhoff et al., 2018). Positive (vs. negative) words also occur more frequently in various written and spoken languages (Augustine et al., 2011; Dodds et al., 2015).

Second, negative attributes are more diverse than positive attributes, meaning that there are more ways to be bad than there are ways to be good (Alves et al., 2016; 2017b; Koch et al., 2016; Unkelbach et al., 2008). One reason for the diversity asymmetry is that on most attribute dimensions, there is only one positive range that is rather moderate. At the same time, there is a negative range of insufficiency and a negative range of excess, a principle already recognized by Aristotle (ca. 350 B.C.E./1999). For example, low scores on conscientiousness (C), extraversion (E), and openness (O) constitute the negative features of absentmindedness, shyness, and rigidity, respectively. Moderate scores constitute the positive features of conscientiousness etc. And high scores constitute the negative features of pedantry, intrusiveness, and recklessness, respectively. When several attribute dimensions are combined into a personality, a diverse range of possible negative personalities emerges, while the likable personality is narrowly defined (Alves et al., 2017b; Carter et al., 2018; Grant & Schwartz, 2011; Imhoff & Koch, 2017).

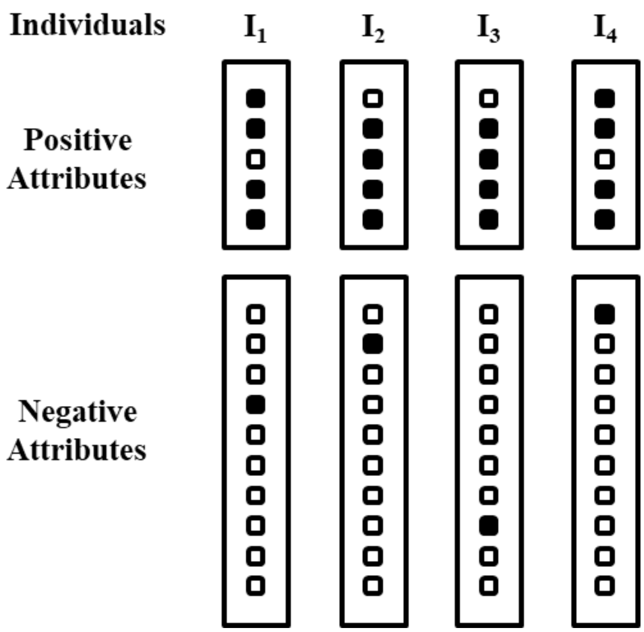
The combination of the two ecological assumptions that people typically possess more positive than negative attributes and that there are a larger number of possible negative attributes implies that the probability for a given positive attribute to be present in a person is higher than the probability for a given negative attribute to be present in a person ($p(pos_i) > p(neg_i)$)[1]. Thus, positive attributes tend to be shared among individuals, while an individual's negative attributes tend to be distinct (for a formalization, see Alves et al., 2017a; 2018; Baldwin et al., 2023).

Figure 1 illustrates this statistical necessity in a simple feature model (Tversky, 1977). Depicted are attribute vectors of four individuals. Within each individual, certain positive and negative attributes can be present (filled squares) or absent (unfilled squares). The assumed higher overall frequency of positive attributes is modeled here, as for each individual the ratio of present positive attributes to present negative attributes is four to one. The greater diversity of negative attributes is modeled as the vector of possible negative attributes that individuals can possess is twice as long as the vector of positive attributes.

[1] Note that the overall higher frequency of positive attributes already implies that any positive attribute is on average more likely to be present in an individual than any negative attribute if one assumes no diversity asymmetry. Likewise, the diversity asymmetry already implies a higher likelihood for any positive (vs. negative) attribute to be present in an individual if one assumes no frequency asymmetry. The combination of the asymmetries that positive attributes are overall more frequent and that negative attributes are more diverse implies a strong asymmetry in the probability that positive and negative attributes are present.

Figure 1

Illustration of the frequency and diversity asymmetries in the evaluative information ecology



Note. Filled squares represent present attributes, and unfilled squares represent absent attributes.

As a result of these two asymmetries, the probability for any positive attribute to be present in an individual is considerably higher ($p(pos_i) = .80$) than the probability for any negative attribute to be present in an individual ($p(neg_i) = .10$). This also means that a positive attribute present in individual 1 is much more likely to be shared by another individual 2 ($p = .80$) than a negative attribute present in individual 1 is likely to be shared by another individual 2 ($p = .10$). Conversely, a negative attribute present in individual 1 is much more likely to be distinct (i.e., unshared by individual 2; $p = .90$) than a positive attribute present in individual 1 ($p = .20$). Thus, a sample of distinct attributes that differentiate a given individual from others is necessarily negatively biased. Consequently, any cognitive process that prioritizes distinct (vs. redundant) attributes will overemphasize negativity.

Serial Position, Distinctiveness, and Negativity

To reiterate, the cognitive principle of differentiation implies that when people sequentially describe individuals, their descriptions of later-encountered individuals will primarily cover distinct attributes that differentiate them from earlier-encountered persons. This means that their descriptions will become more and more distinct. If we combine this insight with our assumptions about the evaluative information ecology, namely that negative attributes are overrepresented among distinct attributes of people, we can predict that person descriptions should also become more negative as sequential encounters progress.

We conducted a simulation to further illustrate the model's assumptions and predictions and to anticipate the analyses in the present research. The general set-up of the simulation was similar to the models' illustration in Figure 1. We first simulated attribute vectors for 20 target persons that could potentially display 20 positive attributes and 60 negative attributes, realizing the assumption of a greater diversity of negativity. For each target person, the simulation randomly determined which of the positive and negative attributes were present and which were absent in that target. We realized the assumed higher frequency of positive attributes, as each target had 16 positive attributes and 12 negative attributes on average. These diversity and frequency asymmetries then implied that the probability for each positive attribute to be present in each target was $p = .8$, and the probability for each negative attribute to be present was $p = .2$. After the attribute vectors for all targets were determined, the simulation randomly picked one "descriptor" attribute from the attributes present in the first target. This descriptor attribute has a higher likelihood of being positive than negative ($p = .57$). The simulation then randomly determined one of the next target's attributes as the descriptor with one restriction. If the descriptor had already been used as a descriptor for one of the previous targets, the simulation re-sampled the descriptor, thereby realizing the assumed differentiation principle. The sampled descriptors for all 20 targets were stored in a vector, and another vector coded whether each target's descriptor was positive or negative.

This simulation was run 10,000 times, each simulation trial representing one perceiver who describes the 20 targets. The simulation program then calculated the average probability for each of the 20 targets that its descriptor was negative. As predicted by our model, this probability increased with increasing serial position of the target. Next, the program calculated the probability for each of the 80 attributes that it was used as a descriptor across all 10,000 simulation trials. This measure determined the attributes' overall description distinctiveness, where larger values mean that the attribute is a rather redundant descriptor and smaller values mean that the descriptor is rather distinct. The program then iterated through all 20 targets within each simulation trial and determined the overall distinctiveness of each target's descriptor. In a final step, the program calculated the average overall descriptor distinctiveness for each target across all simulation trials. As predicted by our model, the distinctiveness of the descriptors increased with increasing serial position of the targets. In other words, later-encountered targets had a higher probability of being described with attributes that are overall rarely used as descriptors (i.e., more distinct).

In sum, the simulation confirmed that if we assume a greater diversity of negative attributes, a higher frequency of positive attributes, and a differentiation rule by which perceivers avoid using descriptors twice, later-encountered targets are more likely to be described with negative and with overall more distinct attributes. Finally, the effect of serial position on attribute valence was accounted for when a mediation model included descriptor distinctiveness as a mediator. The results of this simulation can be found in Table 8 in the supplementary materials.

It is important to note that the simulated serial position-negativity effect is not exclusive to the assumption that perceivers avoid re-using an attribute that they have already used as a descriptor for previous targets. Instead, the serial position-negativity effect also follows if perceivers avoid describing a given target with any attribute that they have noticed in previous targets from the same series. As long the presence of an attribute in a perceiver's descriptions or impressions of targets lowers its likelihood of being used as a descriptor of later targets from the same series, the serial position-negativity effect follows.

The illustrated serial order effects have several consequential implications for real life. Job interviews and other performance evaluations such as online dating are typically sequential events in which perceivers are confronted with several target persons in a given sequential order. If descriptions of later-encountered targets do indeed become more negative, this could trickle down to an early-bird advantage. For example, consider a hiring committee that discusses the impression that each candidate made after their interview. The first few candidates may be described in rather positive terms, while the differentiation principle will force descriptions of subsequent candidates to become more and more negative.

The Present Research

The present work further tested the cognitive-ecological model of person perception, which predicts a serial order-negativity effect in person descriptions, a phenomenon with real-world implications. This work extends previous research on the cognitive-ecological model as follows. First, previous research has empirically confirmed the differentiation principle at the levels of choice formation, evaluation, and memory content (e.g., Alves et al. 2018; 2020; Bruine de Bruin & Keren, 2003; Hodges, 1997; Houston et al., 1989; Houston & Sherman, 1995). It has not yet been tested whether the principle also applies at the communication level, specifically person descriptions. Second, previous research has shown differentiation only among rather short stimulus sequences with a maximum of four target stimuli. In the present work, we realized sequences of five, ten, or twenty targets to test whether differentiation effects generalize to longer sequences, which regularly occur in real-life (e.g., hiring committees, sports and music performance evaluations, and online dating). Third, previous research is confined to paradigms that present fictional stimuli (e.g., brands, products, or persons) and verbally describe their attributes. These experiments manipulated whether positive or negative attributes are shared or distinct. In the present work, we also manipulated differentiation (vs. assimilation) behavior directly and used representatively sampled real-world stimuli (i.e., Facebook profile pictures and video clips from a TV show). Thus, we relied on the assumed distinctiveness asymmetry inherent in the natural information ecology (i.e., distinct attributes tend to be negative rather than positive). Hence, the present work generalizes the cognitive-ecological model to the domain of person descriptions and establishes the ecological validity of the model.

Overview of the Studies

In Study 1, we drew a representative sample of 1,000 target individuals as they appeared in their Facebook profile pictures in 2021. Perceivers described one feature of each target in a series of twenty randomly selected targets. We predicted that perceivers would describe later-encountered targets with more distinct and negative features. Study 2 predicted that instructing participants to find similarities among targets would eliminate the indirect effect (from later to distinct to negative description) that we predicted to find in a control condition. Study 3 aimed to generalize the serial position-negativity effect to multi-sentence descriptions of videos showing target persons as they appeared in a recent season of the TV show The Bachelor. In Study 4, participants described one of two subsets of Facebook profile pictures. One subset consisted of the most positive pictures, and the other consisted of the most negative pictures. According to our cognitive-ecological model, positive attributes should become more distinct among a subset of portraits with mostly negative attributes, and the serial order-negativity effect should thus be attenuated or even reversed. Studies 5a and 5b manipulated the distinctiveness of target persons' positive and negative attributes. Specifically, participants described a series of positive or negative targets that were either highly distinct from one another or highly similar to one another. According to our cognitive-ecological explanation, description valence should not change over a series when targets are sufficiently distinct. However, descriptions should be more negative over the series of positive-similar targets, and more positive over the series of negative-similar targets. Finally, Study 6 tested whether the serial position-negativity effect is not restricted to person descriptions but also applies to mere evaluations of the described targets.

In total, we recruited more than fifteen thousand U.S. residents as participants who described some of one thousand Facebook profile pictures or video clips from the TV show The Bachelor depicting other U.S. residents in 2021. We analyzed the data with linear mixed models that treated both the perceivers and the targets as random samples. This allowed simultaneously generalizing findings to other U.S. residents who come across other U.S. residents on social media platforms or when watching TV.

General Method

All studies were IRB-approved and preregistered (link for Study 1; link for Study 2; link for Study 3; link for Study 4; link for Study 5a; link for Study 5b; link for Study 6) and we report all conditions and measures. Because our studies featured representatively sampled stimuli that we intended to analyze with linear mixed models, we aimed for large sample sizes in all studies. At the same time, we also had to keep the resulting study costs in an affordable range.

This resulted in the collection of at least 1,000 participants for all studies with only one between-participants condition (Studies 1 and 3). For all studies with two between-participants conditions we recruited at least 500 participants per condition (Studies 2 and 4-6). We conducted a simulation-based post-hoc power analysis for linear mixed models (Green & MacLeod, 2015), which estimated that achieved power was never lower than .72 for observing a standardized effect size of b = .05 when setting the α-threshold to .05. The value b = .05 corresponds to the mean sizes of the main effects of serial order on descriptor valence, descriptor distinctiveness, and overall evaluation that we observed in the present research.

For Studies 2, 3, and 6, we preregistered to exclude participants who would finish the studies extremely quickly. To be consistent, we applied this exclusion criterion in all studies. The cut-offs were 240 seconds (Study 1), 145 seconds (Study 2), 300 seconds (Study 3), 240 seconds (Study 4), 120 seconds (Study 5a), 120 seconds (Study 5b), and 45 seconds (Study 6). These were determined upon visual inspection of the duration distributions in the respective studies. The resulting exclusions never concerned more than 2% of a study sample and including these cases in the analyses did not change any results in a meaningful way. We standardized all independent variables within-participants and modeled random effects for the participants and stimuli on all dependent variables, which we standardized around the grand mean. This allowed direct comparison of effect sizes across studies. All figures show unstandardized means, to facilitate interpretation. All study materials, data, code, and results are available on the website of the Open Science Foundation (OSF; link or see Woitzel et al., 2023).

Study 1

Study 1 serially presented participants with 20 Facebook profile pictures and asked them to describe the person depicted in each photo. Study 1 tested three predictions derived from our cognitive-ecological model. First, perceivers' descriptions of targets should become increasingly distinct with increasing serial position of the target. Second, descriptions should become increasingly negative. Third, the relation between serial position and negative description should be accounted for by description distinctiveness.

Methods

Participants. Study 1 sampled 1,003 people from the online platform Prolific Academic. As preregistered, we excluded people whose descriptions were blank or nonsensical. We also excluded six speedsters who completed the study in less than 240 seconds. The final sample was 992 people (445 female, 533 male, 14 other; M_{age} = 37.57 years, 95% CI = [36.72, 38.41]).

Stimuli. In 2021, the online platform Facebook had hundreds of millions of users that resided in the U.S. Study 1 quasi-randomly selected 1,000 of them. We sampled as targets their publicly accessible profile pictures. Specifically, we (1) entered a randomly selected U.S. city into Facebook's search engine, (2) selected the first Facebook page result that (a) was not the city's page, (b) was based in the U.S., and (c) had at least 300 likes from users. Then, we (3) selected the profile photo of the first publicly visible like-expressing person (a) who was the only or focal person in the photo, (b) whose gender, age, and race were discernible, and (c) who resided in the U.S. as evidenced by "lives in […]" or "works at […]" information. We coded the gender, age, and race/ethnicity of the target persons, and estimated 625 women and 375 men. There were 327, 518, and 155 people whose age we estimated to be under 30 years, 30-60, and above 60, respectively. We estimated that there were 815 White people, 89 Black people, 51 Latino/a people, 28 East Asian people, and 17 South Asian people.

Procedure. For each perceiver, Study 1 randomly selected 20 of the 1,000 pictures. Perceivers described the 20 targets in the pictures on 20 separate screens and in random order.

On each screen, perceivers' instructions were: "Form an impression about the person in this Facebook profile picture. [The photo appeared below, and the following instructions appeared below the photo.] Type in a description of the person in the above picture. No slang, no typos, and one word only (two words connected with a hyphen is okay)."

After describing the 20 targets, perceivers rated the distinctiveness and valence of the 20 descriptions they had used in random order. Perceivers used a 7-point scale ranging from "very uncommon (unique)" to "very common" to rate the distinctiveness of the descriptions one below the other in random order. Note that low values correspond to high distinctiveness, while high values correspond to low distinctiveness. Their instructions were "for each of the following descriptions you provided, please rate how common each descriptor is. Very common descriptions are those that could apply to many people; very uncommon descriptions (unique) are those that apply to only a few people." Perceivers used a 7-point scale ranging from "very negative (bad)" to "very positive (good)" to rate the valence of the descriptions one below the other in random order; "for each of the following descriptions you provided, please rate how positive or negative each descriptor is. Positive descriptions are good, favorable, or desirable characteristics. Negative descriptions are bad, unfavorable, or undesirable characteristics."

Finally, perceivers indicated their age, gender, ethnicity, socioeconomic status, and ideology ranging from conservative to progressive (Koch et al., 2016).

Measures. As preregistered, Study 1 excluded 84 blank descriptions and 20 nonsensical ones. Preprocessing the remaining 19,836 descriptions included cutting whitespace, standardizing punctuation, and using the R package hunspell (Ooms, 2020) to spell-check and correct the descriptions. After correcting spelling, 3,209 different descriptions remained.

Description Distinctiveness. We used three different measures of description distinctiveness. First and primarily as preregistered, we assessed each description's frequency among the 19,836 descriptions that participants had provided (*situational objective* distinctiveness). We reduced the strong skewness of this measure by log-transforming it. As a second distinctiveness measure, we assessed the frequency of the 3,209 different descriptions among hundreds of billions of words scraped from publicly accessible websites in 2006 (*universal objective* distinctiveness). We again reduced the strong skewness of this measure by log-transforming it. Participants' distinctiveness ratings of the descriptions they had provided served as the third measure (*universal subjective* distinctiveness), and we calculated the mean value of these ratings for each of the 3,209 different descriptions. Note again that low values on the distinctiveness measure correspond to high distinctiveness, while high values correspond to low distinctiveness.

Description Valence. We used two measures to assess the *universal subjective valence* of the 3,209 descriptions. The first, primary, and preregistered measure was based on previous research by Warriner and colleagues (2013), who report mean ratings for 13,915 words on a valence scale ("[makes me feel] unhappy" = 1, "[…] happy" = 9). If a description appeared in the database by Warriner and colleagues, we assessed its valence based on its mean rating in the database. If it did not appear in the database but its word stem appeared in the database, we assessed its valence based on the mean rating for its word stem suggested by the R package hunspell (Ooms, 2020). If its word stem did not appear in the database, we assessed its valence based on the mean ratings for up to ten of its synonyms suggested by the R package wordnet (Feinerer & Hornik, 2020). If no synonym suggested like this appeared in the database, we assessed its valence based on the mean ratings for up to five synonyms suggested by Python code that represents the meaning of all words in the vast Google News text corpus in a 300-dimensional space. If no synonym suggested like this appeared in the database, we ran through this stepwise process for all parts of the description (if it had parts; e.g., we ran through the process for both "beautiful" and "hat" if the description was "beautiful-hat") and then averaged valence across all description parts. In all, Study 1 measured the positivity of 3,188 of the 3,209 different descriptions (99.3%).

The second measure of description valence was based on our participants' mean ratings of the valence of the descriptions they had provided.

Results

First, we assessed whether participants' descriptions of the first target they encountered were predominantly positive as assumed by our model. The mean valence of participants' first description was M = 6.19, 95% CI = [6.08, 6.30], on a scale from 1 to 9 according to our primary measure, and M = 5.13, 95% CI = [5.04, 5.23], on a scale from 1 to 7 according to our secondary measure (participants' own evaluation). Hence, participants assigned mostly positive person descriptions to the representatively-sampled Facebook profile pictures at first sight[2], confirming one of our model's central ecological assumptions (see Figure 1). Next, we aimed to assess the central cognitive assumption of the model, namely that people naturally differentiate others when they describe them sequentially. We found that participants indeed used the vast majority (88.7%, 95% CI = [87.8%, 89.5%]) of their descriptors uniquely, only to describe one target[3].

[2] Table 6 in the supplementary materials shows that the first person description was more on the positive side in all conditions of all studies, except when we had manipulated the ecology of target persons to be negative – then the first person description was more on the negative side in all cases except one.
[3] Table 7 in the supplementary materials shows that participants provided mostly distinct, unique person descriptions in all conditions of all studies, except when we had instructed them to find similarities between target persons by repeating their already-used person descriptions.

We then ran three preregistered linear mixed models with the primary measure of description valence or distinctiveness as the dependent variable, and with serial position and distinctiveness as independent variables, and random intercepts for the perceivers and the targets they described. Model 1.1 in Table 1 found that perceivers' descriptions became increasingly negative with increasing serial position. Model 1.2 found that perceivers' descriptions also became increasingly distinct. Model 1.3 included valence as the dependent variable, and serial position and distinctiveness as independent variables. In this model, serial position was not a significant predictor of description valence anymore, whereas the effect of distinctiveness was significant. The results of Models 1.1-1.3 were consistent with an indirect effect from serial position to description distinctiveness to description valence (-0.063 * 0.296 = -0.019).

Table 1

Study 1: Effect of later description on negative description through distinct description

M	IV	DV	*b* and 95% CI	*t*	*p*
1.1	Serial position	Valence	-0.018 [-0.030, -0.005]	-2.79	.005
1.2	Serial position	Distinctiveness	-0.063 [-0.076, -0.050]	-9.59	< .001
1.3	Serial position	Valence	0.003 [-0.009, 0.015]	0.54	.593
1.3	Distinctiveness	Valence	0.296 [0.284, 0.308]	47.83	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

We reran Models 1.1-1.3 with modifications. Models 1.4-1.6 replaced log-transformed situational objective distinctiveness with raw situational objective distinctiveness.

Models 1.7-1.9 replaced log-transformed situational objective distinctiveness with log-transformed universal objective distinctiveness (the second distinctiveness measure). And Models 1.10-1.12 replaced log-transformed situational objective distinctiveness with universal subjective distinctiveness (the third distinctiveness measure), and replaced the primary measure of universal subjective valence with the second measure of universal subjective valence. Table 1 in the supplementary materials reports the results of Models 1.4-1.12. The results were all consistent with the interpretation that later descriptions were increasingly negative because they were increasingly distinct.

Discussion

Study 1 confirmed the prediction that later-encountered target persons are described with more distinct attributes than earlier-encountered targets, which aligns with the assumed differentiation principle. In addition, descriptions became increasingly negative with increasing serial position of the targets. Finally, the increasing distinctiveness of person descriptions could account for the increasing negativity of descriptions, as predicted by our ecological assumptions that negative attributes are overrepresented among distinct attributes.

It is important to note that Study 1's regression results only constitute necessary but not sufficient conditions to infer a causal direction according to which the perceivers' goal to differentiate the targets causes them to describe later-encountered ones with overall more distinct attributes and therefore with more negative attributes. Study 2 tested the assumed causal role of perceivers' differentiation goal more directly.

Study 2

To test the causal role of cognitive differentiation as assumed in our model, Study 2 added a novel "assimilation" condition in which participants were instructed to find similarities among the target persons they described. If successful, this manipulation should counter participants' differentiation tendencies with the opposite tendency of finding shared attributes among targets. If differentiation indeed causes later-encountered targets to be described with more distinct and thus more negative attributes, these effects should be reduced or eliminated in the assimilation condition. In a control condition, participants were simply asked to describe the target persons as in Study 1, which should again give rise to differentiation tendencies. Finally, Study 2 also assessed how aversive or pleasant participants felt about the description task, to test the possibility that participants who got annoyed with the task used increasingly negative descriptors later in the task.

Methods

Participants. Study 2 sampled 4,015 people from Prolific. As preregistered, we excluded people whose descriptions were blank or nonsensical. We also excluded 28 speedsters who completed the study in less than 145 seconds. The final sample was 3,987 people (1,903 female, 1,974 male, 110 other; M_{age} = 39.59 years, 95% CI = [39.08, 40.09]).

Stimuli. Perceivers described the same 1,000 targets as in Study 1.

Procedure. The first of three differences between Studies 1 and 2 was an additional instruction in the assimilation condition. For each target, perceivers read, "Your task is to find many similarities between the people you describe. To tag a similarity, simply repeat a description you have used before." The second difference was that after describing the 20 targets, perceivers rated neither the distinctiveness nor the valence of the 20 descriptions they had used. Instead, they used 7-point scales ranging from "I disagree completely" to "I agree completely" to rate how aversive (pleasant) they found the person description task. Four scales measured the negative experiences "This study was boring," "[…] tiring," "[…] annoying," and "[…]

frustrating", and four more scales measured the positive experiences "This study was exciting," "[…] thrilling," "[…] pleasant," and "[…] motivating." Finally, people indicated their age, gender etc. as in Study 1.

Measures. As preregistered, Study 2 excluded 24 blank or nonsensical descriptions and corrected spelling as in Study 1.

Description Distinctiveness. Studies 1 and 2 used the same primary measure of description distinctiveness (infrequency among all descriptions provided by all perceivers).

Description Valence. Studies 1 and 2 used the same primary measure of description valence (the one that leveraged the large database of mean ratings of word valence).

Aversiveness of the task. For each participant, we subtracted from their mean rating of the negativity of the task their mean rating of its positivity.

Results

Similar to Study 1, participants in the control condition used mostly unique person descriptions that they never repeated (88.3%, 95% CI = [87.6%, 89.0%]). This rate was substantially lower for participants in the assimilation condition (41.5%, 95% CI = [40.6%, 42.5%]). Thus, our manipulation successfully reduced participants' natural tendency to differentiate the targets that they described in a series.

We ran two preregistered linear mixed models with random intercepts for the perceivers and targets. Model 2.1 in Table 2 included description valence as the dependent variable, condition (0 = control, 1 = assimilation; dummy-coded), serial position, and their interaction as independent variables. Model 2.2 replaced valence with description distinctiveness as the dependent variable. The interaction effects in both models were significant. We then recalculated the distinctiveness of each description within each of the two conditions (control vs. assimilation), and we ran three models in both conditions.

Table 2

Study 2: The effect of later on negative through distinct description vanished when perceivers assimilated (vs. differentiated) the target persons they described

M	IV	DV	*b* and 95% CI	*t*	*p*
2.1	Goal	Valence	0.175 [0.149, 0.201]	13.39	< .001
2.1	Serial position	Valence	-0.012 [-0.020, -0.004]	-2.92	.003
2.1	Goal * Position	Valence	0.019 [0.007, 0.031]	3.13	.002
2.2	Goal	Distinctiveness	0.444 [0.415, 0.474]	29.43	< .001
2.2	Serial position	Distinctiveness	-0.085 [-0.094, -0.077]	-20.35	< .001
2.2	Goal * Position	Distinctiveness	0.112 [0.100, 0.124]	18.51	< .001
Goal = Control					
2.3	Serial position	Valence	-0.012 [-0.021, -0.004]	-2.88	.004
2.4	Serial position	Distinctiveness	-0.082 [-0.091, -0.073]	-17.98	< .001
2.5	Serial position	Valence	0.015 [0.007, 0.023]	3.76	< .001
2.5	Distinctiveness	Valence	0.319 [0.311, 0.328]	75.80	< .001
Goal = Assimilation					
2.6	Serial position	Valence	0.007 [-0.001, 0.015]	1.69	.092
2.7	Serial position	Distinctiveness	0.029 [0.021, 0.037]	6.98	< .001
2.8	Serial position	Valence	-0.006 [-0.013, 0.002]	-1.48	.139
2.8	Distinctiveness	Valence	0.341 [0.333, 0.349]	82.16	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

As shown in Table 2, perceivers' later descriptions were increasingly negative (Model 2.3) and increasingly distinct (Model 2.4) in the control condition. In a model with description valence as the dependent variable and serial position and distinctiveness as simultaneous predictors (Model 2.5), serial position was not a significant predictor of descriptor valence anymore, while distinctiveness remained a significant predictor. These results are consistent with an indirect effect from later to distinct to negative descriptions (-0.082 * 0.319 = -0.024), which replicated Study 1 and empirically supported our model's predictions.

In the assimilation condition, perceivers' later descriptions trended towards being increasingly positive (Model 2.6), and they were increasingly less distinct (Model 2.7). When predicting description valence from both serial position and distinctiveness, the serial order trend disappeared, while distinctiveness remained a significant predictor (Model 2.8).

Table 2 in the supplementary materials shows that participants who found the task more aversive (more boring, annoying etc., or less exciting, pleasant etc.) than pleasant provided more negative person descriptions in both conditions. However, participants' experienced aversiveness did not moderate the serial order effect on descriptor valence in any of the two conditions.

Discussion

Study 2's control condition replicated Study 1's findings that participants generally avoided using descriptors twice, and they described later-encountered target persons with more distinct and more negative attributes. Importantly, descriptor distinctiveness again accounted for the effect of serial position on descriptor valence. Study 2's assimilation condition successfully reduced participants' differentiation tendencies as participants used more than half of all descriptors at least twice. Crucially, this eliminated and even partly reversed the results pattern we observed in Study 1 and Study 2's control condition. In line with our model, these findings suggest that perceivers' differentiation tendencies are a necessary condition for the serial position-negativity-effect, and for its mediation through distinctiveness, to occur. This supports our model's central claim that differentiation causes later-encountered targets to be described with more distinct and thus more negative attributes.

Study 3

So far, we have found evidence for an indirect effect from serial position to distinct to negative descriptions for profile pictures of target persons described with one word. Study 3 tested whether the effect generalizes to cases where perceivers view video clips of target persons and describe them with multiple sentences.

Participants. Study 3 sampled 1,011 people from Prolific. As preregistered, we excluded people whose descriptions were blank or nonsensical. We also excluded two speedsters who completed the study in less than 300 seconds. The final sample consisted of 987 participants (441 female, 524 male, 22 other; M_{age} = 41.56 years, 95% CI = [40.73, 42.40]).

Stimuli. Perceivers described 10 women who appeared in a public-facing video excerpt from a recent season of the U.S. version of the TV show The Bachelor. In each of 10 video clips that played between 10 and 15 seconds, one woman introduced herself to a man in a creative, attention-seeking way aiming to get a marriage proposal from him at the end of the season/show.

Procedure. The ten video clips were presented to each participant in a randomized order. For each target, perceivers read: "Form an impression of the woman in the video. Think of a way to describe this woman. Type in that description (no slang, no typos, 100-200 characters long)." To give an example, one participant described one target person with "[Name] seems like a humorous person. Her introduction was funny, and she comes off as charming rather than arrogant."

After that, participants rated the aversiveness of the task in the same way as in Study 2. Finally, participants indicated their age, gender, ethnicity, socioeconomic status, and ideology.

Measures. As preregistered, Study 3 excluded 22 blank or nonsensical descriptions and corrected spelling as in Study 1.

Description Distinctiveness. Study 3 used the same primary and secondary measures of description distinctiveness as Study 1 (infrequency among all descriptions provided by all perceivers, and infrequency among all words scraped from the internet as in Study 1), except that we averaged distinctiveness across all typed words that were not helper words ("a," "an," "with," etc., see Table 10 in the supplementary materials) separately for each description.

Description Valence. Studies 1-3 used the same primary measure of description valence (the one that leveraged the large database of mean ratings of word valence), except that in Study 3 we averaged valence across all typed words that were not helper words separately for each description. In addition, we used the R package sentimentR (Rinker, 2022) to measure the valence of each description in a sophisticated way that understands negation and modification ("not great" and "very good").

Aversiveness of the task. Studies 2 and 3 used the same measure of aversiveness.

Results

We ran the same three linear mixed models with random intercepts for the perceivers and targets as in Study 1. As shown in Table 3, perceivers' later descriptions were increasingly negative (Model 3.1 and Figure 2) and increasingly distinct (Model 3.2). In a model with description valence as the dependent variable and serial position and distinctiveness as simultaneous independent variables (Model 3.3), perceivers' later descriptions were not increasingly negative anymore, while distinctiveness remained a significant predictor. These results are consistent with the hypothesized indirect effect from later to distinct to negative descriptions (-0.052 * 0.257 = -0.013).

Table 3

Study 3: The indirect effect from later to distinct to negative description when perceivers used 1-3 sentences to describe target persons that appeared in short video clips

M	IV	DV	*b* and 95% CI	*t*	*p*
3.1	Serial position	Valence	-0.034 [-0.052, -0.016]	-3.68	< .001
3.2	Serial position	Distinctiveness	-0.052 [-0.067, -0.037]	-6.72	< .001
3.3	Serial position	Valence	-0.016 [-0.034, 0.001]	-1.86	.063
3.3	Distinctiveness	Valence	0.257 [0.240, 0.274]	28.82	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Figure 2

Results of Study 3

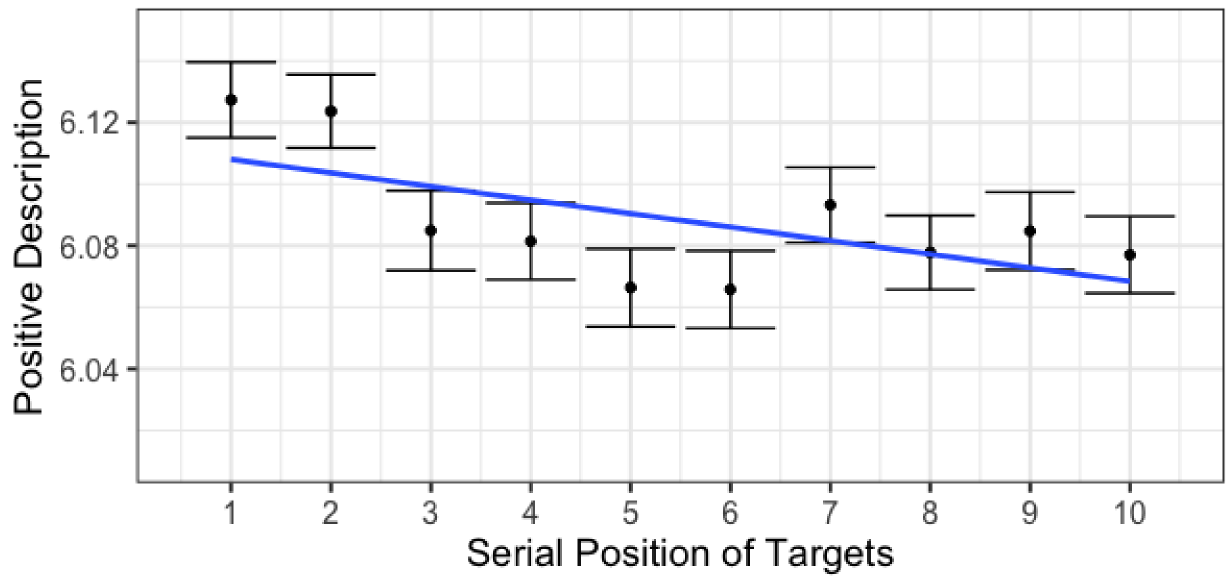


Table 3 in the supplementary analysis shows that this pattern of results did not replicate when we replaced our primary measures of description distinctiveness with our secondary measure (infrequency among all words scraped from the internet as in Study 1). However, the pattern of results replicated when we replaced our primary measure of description valence with the sophisticated measure that leveraged the R package sentimentR (Rinker, 2022).

Table 3 in the supplementary materials clarifies the role of participants' experience that the person description task was more aversive (boring, annoying etc.) compared to pleasant (exciting, pleasant etc.). Participants who found the task to be more aversive provided more negative person descriptions. However, as in Study 2, perceived aversiveness did not moderate the effect of serial position on description valence.

Discussion

Study 3 replicated the findings from the previous two studies in a design where participants used multiple sentences to describe target persons who appeared in video clips. This confirms that the serial position-negativity-effect generalizes beyond one-word descriptions of still pictures. It also underlines that the present effects may have a number of real-world implications for scenarios such as job interviews, speed dating, or any kind of televised competitions.

We now turn to boundary conditions for the serial position-negativity-effect that are predicted by the cognitive-ecological model. Note that the ecological part of the model assumes a higher overall frequency of positive attributes and a greater diversity of negative attributes, which implies that positive attributes have a higher probability of being present in a person than negative attributes, and therefore, negative attributes are overrepresented among distinct attributes (e.g., Alves et al., 2022). Thus, if either the frequency or diversity asymmetries are altered in a target sample, the relation between serial position and valence should change accordingly.

Study 4

Study 4 tested whether the overall frequency of target persons' positive and negative attributes constitutes a boundary condition of the serial position-negativity effect. Thus, we created two target subsamples. One sample had predominantly positive targets among which positive attributes should be more frequent than negative attributes, and the other had predominantly negative targets among which the frequency asymmetry should be reversed. In line with the cognitive-ecological model, we predicted an interaction between target valence and the serial position-negativity effect. Among positive targets, we predicted increasingly negative descriptions with increasing serial position, while this relation should be attenuated, eliminated, or even reversed among negative targets. We could not determine whether a complete reversal can be expected for the following reasons. On the one hand, the probability for any negative relative to any positive attribute to be present among negative targets is certainly increased. On the other hand, negative attributes should still be more diverse, which is why the probability that any specific positive attribute is present in a target person could still be higher than the probability that any specific negative attribute is present (see Figure 1). Hence, the degree to which our model predicts a reversal of the serial position-negativity effect among negative targets depends on the relative strengths of the frequency and diversity asymmetries among these targets, which is difficult to determine beforehand. In any case, our model predicts an interaction between serial position and target valence.

Methods

Participants. Study 4 sampled 995 perceivers from Prolific. As preregistered, we excluded people whose descriptions were blank or nonsensical. We also excluded seven speedsters who completed the study in less than 240 seconds. The final sample was 987 people (558 female, 417 male, 12 other; M_{age} = 32.53 years, 95% CI = [31.72, 33.34]).

Stimuli. Perceivers described the targets in 200 of Study 1's pictures. On average, 100 of the targets had been described most positively in Study 1. The other 100 targets had been described most negatively in Study 1, on average. Most positive and negative description was based on the descriptions' mean ratings on Warriner and colleagues' (2013) valence scale.

Procedure. For each perceiver, Study 4 randomly selected 20 of the 100 most positive targets, or 20 of the 100 most negative targets. Perceivers described these targets on 20 separate screens and in random order given the same instructions as in Study 1. Then, they rated the distinctiveness and valence of their descriptions in the same way as in Study 1. Finally, people indicated their age, gender etc.

Measures. As preregistered**,** Study 4 excluded 22 blank or nonsensical descriptions and corrected spelling as in Study 1.

Description Distinctiveness. Studies 1 and 4 used the same primary and tertiary measures of the distinctiveness of perceivers' descriptions of the targets.

Descriptions Valence. Studies 1 and 4 used the same primary and secondary measures of descriptions valence.

Results

Study 4 ran two preregistered linear mixed models with random intercepts for perceivers and the targets they described. Model 4.1 in Table 4 included description valence as the dependent variable, and target person valence (0 = positive, 1 = negative; dummy-coded), serial position, and their interaction as independent variables. Model 4.2 in Table 4 included description distinctiveness as the dependent variable, and target person valence, serial position, and their interaction as independent variables. As shown in Table 4, the interaction effects in both models were significant. We then recalculated the distinctiveness of each description within each of the two target valence conditions, and we analyzed the effects of serial position and description distinctiveness on description valence in both conditions.

As shown in Table 4, perceivers' later descriptions were increasingly negative (Model 4.3 and Figure 3) and increasingly distinct (Model 4.4) when they described a series of positive targets. In a model with description valence as the dependent variable and serial position and distinctiveness as simultaneous independent variables (Model 4.5), serial position was no longer significant, while distinctiveness remained significant. These results are consistent with an indirect effect from later to distinct to negative descriptions (-0.093 * 0.502 = -0.047). Hence, the positive target condition results replicated Study 1 and were consistent with our model's predictions.

Table 4

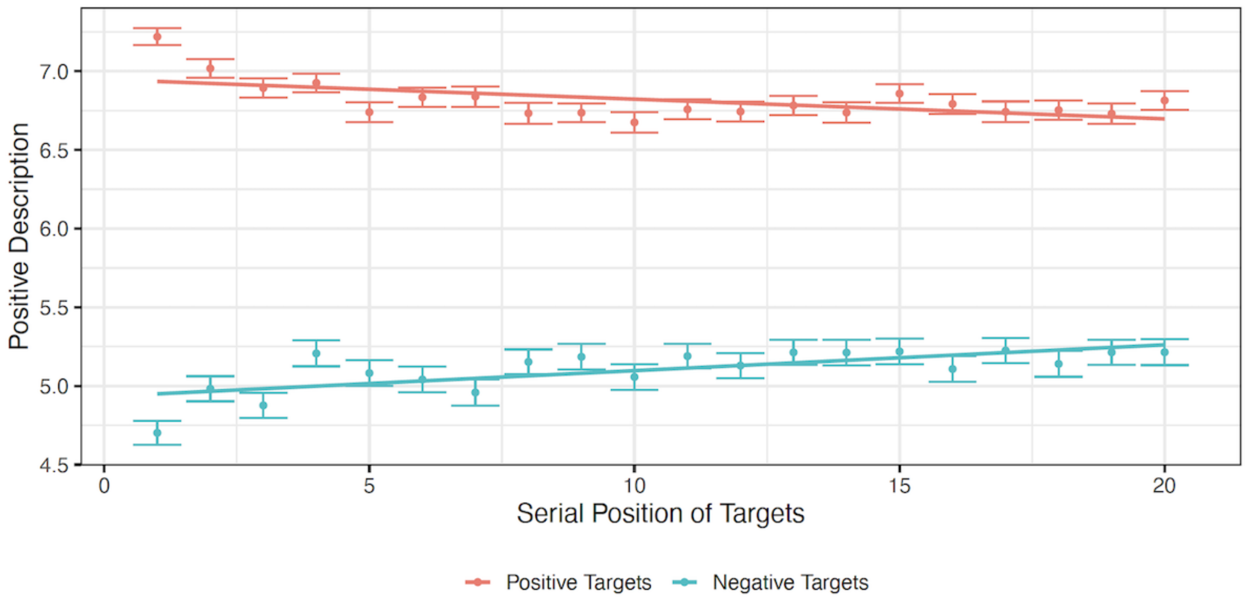
Study 4: The effect of later description on negative description through distinct description was almost zero when perceivers described negative targets rather than positive targets

M	IV	DV	*b* and 95% CI	*t*	*p*
4.1	Target Valence	Valence	-0.936 [-1.017, -0.855]	-22.66	< .001
4.1	Serial position	Valence	-0.041 [-0.057, -0.024]	-4.89	< .001
4.1	Target Valence * Position	Valence	0.092 [0.069, 0.115]	7.86	< .001
4.2	Target Valence	Distinctiveness	-0.299 [-0.372, -0.227]	-8.07	< .001
4.2	Serial position	Distinctiveness	-0.090 [-0.109, -0.072]	-9.77	< .001
4.2	Target Valence * Position	Distinctiveness	0.048 [0.022, 0.073]	3.67	< .001
Target Valence = Positive					
4.3	Serial position	Valence	-0.054 [-0.073, -0.036]	-5.71	< .001
4.4	Serial position	Distinctiveness	-0.093 [-0.111, -0.075]	-10.04	< .001
4.5	Serial position	Valence	-0.004 [-0.020, 0.012]	-0.50	.615
4.5	Distinctiveness	Valence	0.502 [0.486, 0.518]	61.01	< .001
Target Valence = Negative					
4.6	Serial position	Valence	0.051 [0.033, 0.070]	5.56	< .001
4.7	Serial position	Distinctiveness	-0.061 [-0.080, -0.043]	-6.52	< .001
4.8	Serial position	Valence	0.047 [0.029, 0.065]	5.10	< .001
4.8	Distinctiveness	Valence	-0.061 [-0.080, -0.043]	-6.52	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Figure 3

Results of Study 4



As shown in Table 4, perceivers also described negative targets that appeared later with increasingly distinct attributes (Model 4.7), consistent with the assumed differentiation principle. Crucially, descriptions of negative targets became increasingly positive instead of negative with increasing serial position. Hence, the serial position-negativity effect was confined to an ecology where positive attributes are prevalent. While we predicted an attenuation of the serial position-negativity effect, we did not expect a reversal of this effect among negative targets, because negative attributes should still be more diverse than positive attributes (see Figure 1). Yet, unlike the positive target condition, the largest part of this reversed effect was not due to increasing description distinctiveness among later-encountered targets. While distinct (vs. common) descriptions were indeed more positive in the negative target condition (Model 4.8), this effect was much smaller than the reverse relation among positive targets (Model 4.5). Consequently, the indirect effect from later to distinct to positive descriptions in a series of negative targets was also quite small (-0.061 * -0.061 = 0.004), compared to the reversed indirect effect found among positive targets (-0.093 * 0.502 = -0.047).

Models 4.9-4.16 replaced the primary measure of description distinctiveness with the tertiary measure, and replaced the primary measure of universal subjective valence with the secondary measure. Table 4 in the supplementary materials reports the results, which are largely consistent with the results of Models 4.1-4.8 in Table 4 but are less informative because the tertiary measure presumably captured distinctiveness among targets in society (i.e., the total population, see Study 1's methods), whereas Study 4 examined subpopulations of targets that were more positive or more negative than the valence in the total population.

Discussion

Study 4 replicated the serial position-negativity effect among positive targets, and description distinctiveness again accounted for that effect. The fact that this indirect effect from later to distinct to negative descriptions was twice as large (-0.091 * 0.502 = -0.046) as the same effect found in Study 1 (-0.063 * 0.296 = -0.019) is in line with the cognitive-ecological model. Increases in the frequency of positive attributes as in Study 4's positive target condition should increase the likelihood for distinct attributes to be negative.

Also in line with our model, description distinctiveness predicted description valence much worse in the negative target condition (-0.061) versus positive target condition (0.502). Higher frequency of negative attributes in the negative target condition should increase the likelihood for positive attributes to be distinct (i.e., unshared). However, negative attributes should be more diverse even in the negative target condition, which renders negative attributes more distinct. The opposite directions of these two effects may then result in the smaller relation between description distinctiveness and description valence observed in the negative (vs. positive) target condition of Study 4. In other words, the indirect effect from later to distinct to evaluative description was smaller in the negative (vs. positive) target condition.

Somewhat inconsistent with this weaker indirect effect among negative targets, their serial descriptions became more positive the later they occurred in the sequence. This complete reversal of the serial position-negativity-effect may therefore be caused by an additional effect unrelated to descriptor distinctiveness. Perhaps participants shifted their comparison standard over the series of negative target persons. As real target person ecologies are usually predominantly positive as in Study 1, perceivers in the negative target condition may have used more negative descriptions for targets early in the sequence and then lowered their comparison standard as the sequence of negative target persons progressed, resulting in usage of relatively more positive descriptions towards the end of the sequence.

In sum, Study 4 confirmed that the serial position-negativity-effect can only be observed among predominantly positive target persons.

Next, we further tested our model by directly manipulating the distinctiveness/similarity of positive and negative attributes among target persons. If the sequential unfolding of description valence is indeed driven by description distinctiveness, this manipulation should determine the direction that description valence takes along the sequence.

Study 5a

In Study 5a, participants described a series of predominantly positive target persons. In one condition, targets had predominantly positive and similar attributes, while in the other condition, targets had predominantly positive and distinct attributes. Our model predicts that person descriptions only become more negative along a sequence when positive targets have many shared attributes. When positive targets have many distinct attributes, participants should not run out of positive attributes to describe the targets, which should result in an attenuation or a complete elimination of the serial position-negativity effect.

Method

Participants. Study 5a sampled 1,054 participants from Prolific (587 female, 458 male, 9 other; M_{age} = 35.07 years, 95% CI = [34.30, 35.84]).

Stimuli. We used the R package word2vec (Wijffel et al., 2021) to model each description of each positive target from Study 4 as a vector in a 300-dimensional space representing the meaning of all words in the vast Google News text corpus. We averaged all description vectors separately for each of the 100 targets. Within this 300-dimensional space we then calculated the mean Euclidean distance between all targets, determining whether they were described with similar or distinct attributes.

To sample 10 positive targets with many shared attributes, Study 5a used the k-means algorithm to cluster-analyze the description vectors that modeled the 100 positive targets. Study 5a then selected a cluster of 10+ vectors / targets and reduced its size to 10 by deselecting the targets furthest from the cluster's centroid.

To sample 10 positive targets with many distinct attributes, Study 5a selected the two of the 100 positive targets whose vectors were furthest from one another. The vector of target 3 that Study 5a selected was furthest from the average of the vectors of selected targets 1 and 2, and further from the vectors of selected targets 1 and 2 than the 65th percentile of the distances between the vectors of all 100 targets. The vector of selected target 4 was furthest from the average of the vectors of selected targets 1-3 and further from the vectors of selected targets 1-3 than the 65th percentile of the distances between the vectors of all 100 targets. We repeated this procedure until we had a sample of 10 targets with many distinct attributes.

Procedure. Perceivers sequentially described the 10 similar or distinct targets on separate screens and in random order given the same instructions as in Study 1. Next, they rated the description distinctiveness and valence the same way as in Study 1. Study 5a used the same primary and secondary measures of description distinctiveness and valence as Study 1. Finally, participants indicated their gender, age, etc.

Measures. As preregistered**,** Study 5a excluded one blank or nonsensical description and corrected spelling as in Study 1.

Description Distinctiveness. Studies 1 and 5a used the same primary and tertiary measures of the distinctiveness of perceivers' descriptions of the targets.

Descriptions Valence. Studies 1 and 5a used the same primary and secondary measures of description valence.

Results

We specified two preregistered linear mixed models with random intercepts for perceivers and the targets they described. Model 5a.1 in Table 5a included description valence as the dependent variable, and target similarity (0 = distinct, 1 = similar; dummy-coded), serial position, and their interaction as independent variables. Model 5a.2 in Table 5a included description distinctiveness as the dependent variable, and target similarity, serial position, and their interaction as independent variables. Both interaction effects were significant. We then recalculated the distinctiveness of each description within each of the two conditions. We analyzed the effects of serial position and description distinctiveness on description valence separately within each condition.

Table 5a

Study 5a: Effect of later description on negative description through distinct description was almost zero when perceivers described distinct (vs. similar) positive targets

M	IV	DV	*b* and 95% CI	*t*	*p*
5a.1	Target Similarity	Valence	-0.063 [-0.239, 0.113]	-0.70	.491
5a.1	Serial Position	Valence	-0.011 [-0.037, 0.015]	-0.86	.391
5a.1	Similarity * Position	Valence	-0.111 [-0.147, -0.074]	-5.92	< .001
5a.2	Target Similarity	Distinctiveness	-0.094 [-0.273, 0.085]	-1.03	.314
5a.2	Serial Position	Distinctiveness	-0.061 [-0.086, -0.036]	-4.73	< .001
5a.2	Similarity * Position	Distinctiveness	-0.087 [-0.122, -0.051]	-4.78	< .001
Target Similarity = Low					
5a.3	Serial Position	Valence	-0.012 [-0.038, 0.015]	-0.86	.387
5a.4	Serial Position	Distinctiveness	-0.057 [-0.082, -0.031]	-4.34	< .001
5a.5	Serial Position	Valence	0.017 [-0.006, 0.041]	1.44	.150
5a.5	Distinctiveness	Valence	0.440 [0.416, 0.464]	35.54	< .001
Target Similarity = High					
5a.6	Serial Position	Valence	-0.119 [-0.145, -0.094]	-9.19	< .001
5a.7	Serial Position	Distinctiveness	-0.148 [-0.173, -0.123]	-11.54	< .001
5a.8	Serial Position	Valence	-0.035 [-0.057, -0.013]	-3.17	.002
5a.8	Distinctiveness	Valence	0.513 [0.491, 0.535]	45.84	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 5a shows that among similar target persons, participants' descriptions became increasingly negative with increasing serial position (Model 5a.6 and Figure 4) and they became increasingly distinct (Model 5a.7). In a model with valence as the dependent variable and serial position and distinctiveness as independent variables (Model 5a.8), serial position was not significant anymore, whereas distinctiveness remained significant. These results translate into an indirect effect from later to distinct to negative descriptions (-0.148 * 0.513 = -0.076), again in line with our model's prediction.

Figure 4

Results of Study 5a.

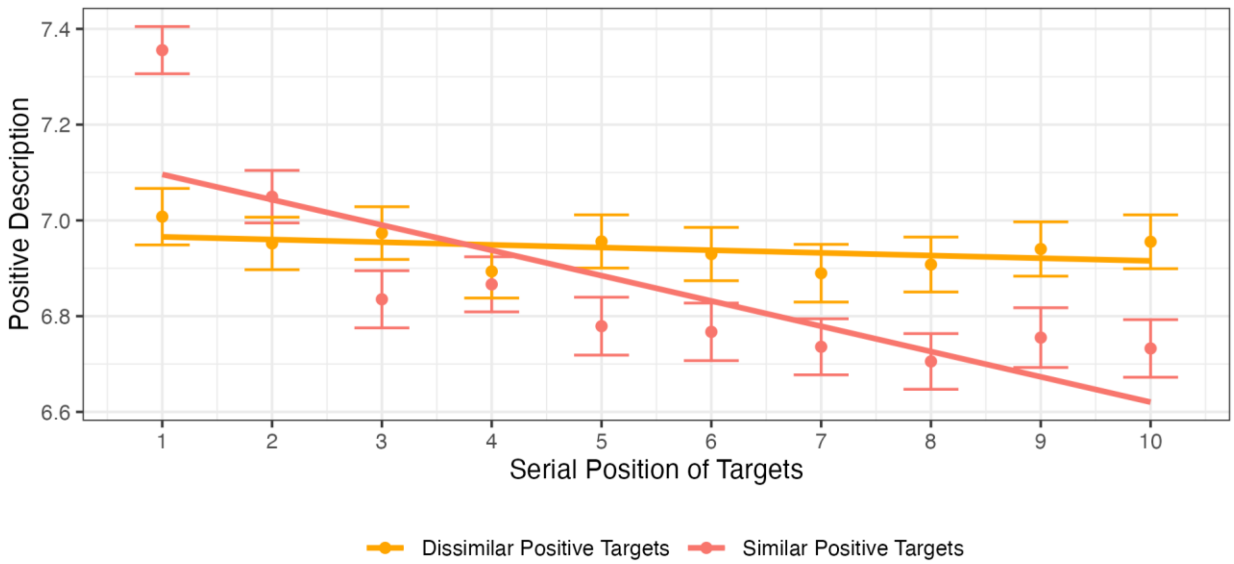


Table 5a also shows that among distinct target persons, description valence did not vary as a function of serial position (Model 5a.3 and Figure 4), even though descriptions still became increasingly distinct with increasing serial position (Model 5a.4). In a model with description valence as the dependent variable and serial position and distinctiveness as independent variables (Model 5a.5), only distinctiveness was a significant predictor. So even though later-encountered targets were described with more distinct attributes, this did not translate into increasingly negative descriptions, supposedly because participants could still find distinct positive attributes as predicted by our model.

Models 5a.9-5a.16 replaced the primary measure of description distinctiveness with the tertiary measure, and replaced the primary measure of universal subjective valence with the secondary measure. Table 5a in the supplementary materials reports the results, which replicated the results of Models 5.1-5.8 in Table 5 but are less informative because the tertiary measure presumably captured distinctiveness among targets in society (i.e., the total population, see Study 1's methods), whereas Study 5a examined a subpopulation of targets that was more positive than the valence in the total population.

Discussion

Study 5a confirmed that target distinctiveness is a boundary condition for the serial position-negativity effect in person descriptions. As predicted by our cognitive-ecological model, person descriptions become more distinct and negative among targets that are positive and have many shared attributes. Here, the differentiation principle forces perceivers to describe later-encountered targets with more negative attributes. When targets have many distinct attributes, the differentiation principle is still visible as perceivers generated more distinct attributes for later-encountered targets. Yet, descriptions did not become more negative. As predicted by our model, perceivers should not run out of positive attributes to describe positive targets if these have enough distinct attributes.

Study 5b

Study 5b was similar to Study 5a except that perceivers described predominantly negative targets with many shared or many distinct attributes. Our model predicts a serial position-positivity effect among similar negative targets because perceivers should likely run out of negative attributes to describe later-encountered targets. The model predicts no serial position effect on description valence among distinct negative targets because perceivers do not run out of distinct negative attributes.

Method

Participants. We recruited 1,054 participants from Prolific (549 female, 495 male, 10 other; M_{age} = 34.20 years, 95% CI = [33.08, 35.31]).

Stimuli. From the 100 negative targets in Study 4, Study 5b sampled 10 targets with many shared attributes, and 10 targets with many distinct attributes, using the same approach as Study 5b.

Procedure. Participants described the 10 distinct negative targets, or the 10 similar negative targets, on 10 separate screens and in random order given the same instructions as in Study 5. Then, they rated description distinctiveness and valence as in Study 1. Studies 5b used the same primary and secondary measures of description distinctiveness and valence as the previous studies. Finally, people indicated their age, gender, etc. as in the previous studies.

Measures. As pre-registered**,** Study 5b excluded one blank description and corrected spelling as in Study 1.

Description Distinctiveness. Studies 1 and 5b used the same primary and tertiary measures of the distinctiveness of perceivers' descriptions of the targets.

Descriptions Valence. Studies 1 and 5b used the same primary and secondary measures of description valence.

Results

We ran two preregistered linear mixed models with random intercepts for perceivers and the targets they described. Model 5b.1 in Table 5b included description valence as the dependent variable, and target similarity (0 = different, 1 = similar; dummy-coded), serial position, and their interaction as independent variables. Model 5b.2 in Table 5b included description distinctiveness as the dependent variable, and target similarity, serial position, and their interaction as independent variables. Both interaction effects were significant. We then recalculated the distinctiveness of each description within each of the two conditions. We analyzed the effects of serial position and description distinctiveness on description valence separately within each condition.

Figure 5

Results of Study 5b.

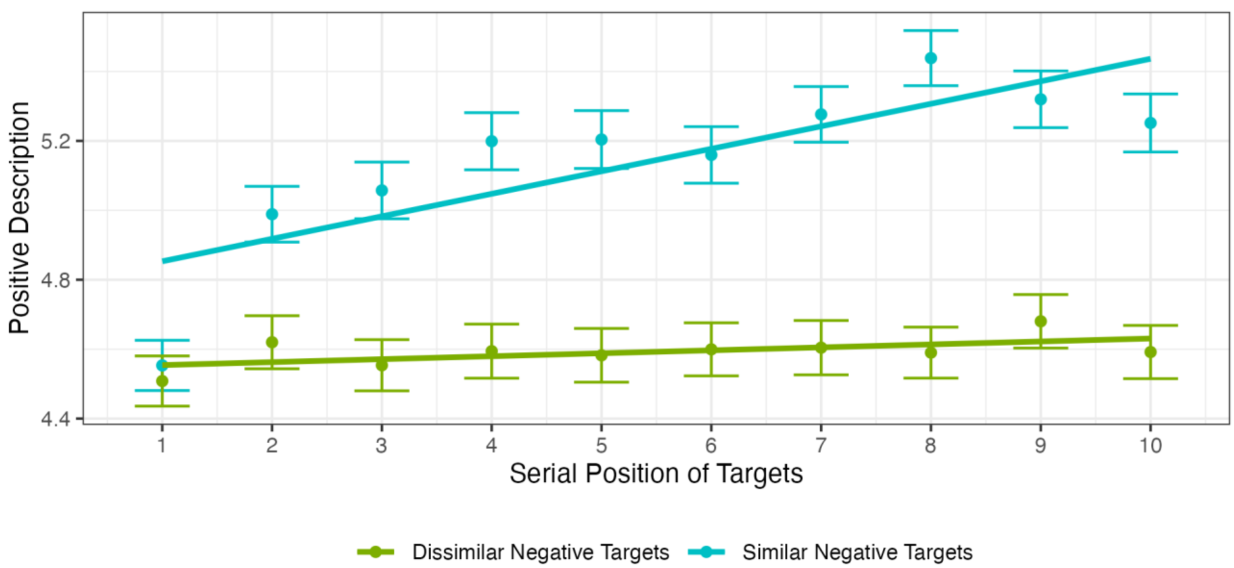


Table 5b shows that participants' descriptions of similar negative targets became increasingly positive (Model 5b.6 and Figure 5) and increasingly distinct (Model 5b.7) with increasing serial position. In a model with description valence as the dependent variable and serial position and description distinctiveness as independent variables, only description distinctiveness was a significant predictor (Model 5b.8). These results translate into an indirect effect from later to distinct to positive descriptions (-0.126 * -0.104 = 0.013) when perceivers described a series of similar negative targets.

Table 5b

Study 5b: Effect of later description on positive description through distinct description was almost zero when perceivers described distinct (vs. similar) positive targets

M	IV	DV	*b* and 95% CI	*t*	*p*
5b.1	Target Similarity	Valence	0.303 [0.000, 0.605]	1.96	.065
5b.1	Serial Position	Valence	0.011 [-0.014, 0.036]	0.87	.382
5b.1	Similarity * Position	Valence	0.095 [0.060, 0.130]	5.29	< .001
5b.2	Target Similarity	Distinctiveness	-0.063 [-0.238, 0.112]	-0.71	.486
5b.2	Serial Position	Distinctiveness	-0.038 [-0.063, -0.013]	-2.93	.003
5b.2	Similarity * Position	Distinctiveness	-0.075 [-0.112, -0.039]	-4.10	< .001
Target Similarity = Low					
5b.3	Serial Position	Valence	0.011 [-0.014, 0.037]	0.89	.373
5b.4	Serial Position	Distinctiveness	-0.041 [-0.067, -0.016]	-3.14	.002
5b.5	Serial Position	Valence	0.006 [-0.019, 0.031]	0.46	.644
5b.5	Distinctiveness	Valence	-0.158 [-0.184, -0.133]	-12.11	< .001
Target Similarity = High					
5b.6	Serial Position	Valence	0.104 [0.079, 0.129]	8.14	< .001
5b.7	Serial Position	Distinctiveness	-0.126 [-0.151, -0.100]	-9.67	< .001
5b.8	Serial Position	Valence	0.091 [0.066, 0.116]	7.05	< .001
5b.8	Distinctiveness	Valence	-0.104 [-0.130, -0.079]	-8.01	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 5b also shows that among distinct negative targets, description valence did not vary as a function of serial position (Model 5b.3 and Figure 5), even though descriptions still became increasingly distinct with increasing serial position (Model 5b.4). In a model with description valence as the dependent variable and serial position and distinctiveness as independent variables (Model 5b.5), only distinctiveness was a significant predictor. Hence, even though later-encountered targets were described with more distinct attributes, this did not translate into increasingly positive descriptions, supposedly because participants could still find distinct negative attributes as predicted by our model.

Models 5b.9-5b.16 replaced the primary measure of description distinctiveness with the tertiary measure, and replaced the primary measure of universal subjective valence with the secondary measure. Table 5b in the supplementary materials reports the results, which were largely consistent the results of Models 5.1-5.8 in Table 5b but are less informative because the tertiary measure presumably captured distinctiveness among targets in society (i.e., the total population, see Study 1's methods), whereas Study 5a examined a subpopulation of targets that was more negative than the valence in the total population.

Discussion

Study 5b again confirmed that target distinctiveness is a boundary condition for the effect of serial position of target persons on the valence of their descriptions. As predicted by our cognitive-ecological model, person descriptions become more distinct and positive among targets that are negative and have many shared attributes. Here, the differentiation principle forces perceivers to describe later-encountered targets with more positive attributes. When targets have many distinct attributes, the differentiation principle is still visible as perceivers generate more distinct attributes for later-encountered targets. Yet, descriptions do not become more positive. As predicted by our model, perceivers should not run out of negative attributes to describe negative targets, as long as these have enough distinct attributes.

The previous experiments have provided consistent evidence for the existence of a serial position-negativity effect in person descriptions resulting from cognitive differentiation. As discussed in the theoretical introduction, differentiation has previously been shown to also guide evaluations of targets such as groups, products, or brands (e.g., Alves et al. 2020; 2018; Bruine de Bruin, 2003; Florack et al., 2021). That is, sequential evaluations of targets are primarily driven by the targets' distinct features that differentiate the targets from previously encountered targets.

However, no study has yet tested a central prediction of the cognitive-ecological model that sequential differentiation renders evaluations of later-encountered targets more negative when targets are representatively sampled. Previous studies on differentiation in evaluations have exclusively relied on manipulating the valence of targets' shared and distinct attributes. The present paradigm allows us to test whether sequential evaluations of representatively sampled target stimuli do indeed become more negative with increasing serial position. In addition, our paradigm allows us to test whether serial order effects on target evaluations are amplified, or only emerge, when perceivers first describe all targets prior to evaluating them. In other words, is communication a necessary component of the serial order-negativity effect? Study 6 tested this.

Study 6

Participants in Study 6 were sequentially presented with a total of five profile pictures from the same stimulus pool as in the previous studies. In a mere evaluation condition, participants were simply asked to indicate how positive or negative their impression of each target was. In a description condition, participants were first asked to describe each target with one word and in a subsequent study phase, they were then asked to evaluate their impressions of the targets. This allowed us to test whether the serial position-negativity effect in the present design extends to mere target evaluations, and whether such evaluation effects are amplified when targets are first described before they are evaluated.

Method

Participants. Study 6 sampled a total of 6,001 participants from Prolific. As preregistered, Study 6 excluded participants whose serial descriptions were blank or nonsensical, and 116 participants who finished the study in less than 45 seconds. The final sample included 5,885 participants (2,926 female, 2,813 male, 146 other; M_{age} = 39.15 years, 95% CI = [38.80, 39.49]).

Stimuli. Perceivers described persons from the same pool of targets as in Study 1.

Procedure. Participants in the mere evaluation condition encountered five targets on five screens and for each target they responded to “How negative or positive is your overall impression of this person?” They answered on a 7-point scale ranging from “very negative (bad)” to “very positive (good)”. Participants in the description condition went through two separate study blocks in which they sequentially encountered the same five targets in the same order. In the first block, participants provided one-word descriptions of the targets akin to Study 1. In the second block, participants reviewed their description of each target and evaluated each target on the same scale and with the same instructions as in the mere evaluation condition. Finally, participants indicated their own age, gender, etc.

Measures. In Study 6, there were no blank or nonsensical descriptions. Spelling was corrected as in Study 1.

Description Distinctiveness and Valence. Study 6 used the same primary measures of description distinctiveness and valence as Study 1.

Results

In a linear mixed model with random intercepts for perceivers and targets, we predicted overall evaluation from condition (0 = pure evaluation, 1 = description before evaluation), serial position, and their interaction as independent variables (Model 6.1). The interaction effect was not significant.

Table 6 shows that perceivers evaluated the targets more negatively when encountering them later in the series. This effect was significant in the mere evaluation condition (Model 6.2) and in the description condition (Model 6.3).

Models 6.4-6.6 focused on the description condition. Model 6.4 showed that perceivers' later descriptions were increasingly distinct. Model 6.5 found that the valence of more distinct descriptions was more negative, while serial position did not predict descriptor valence anymore. Model 6.5 found that more negative descriptions predicted more negative overall evaluations of the targets. These results were consistent with an indirect effect from later to distinct to negative description to negative evaluation (-0.052 * 0.306 * 0.558 = -0.010).

Table 6

Study 6: Effect from later to distinct to negative description to negative evaluation

M	IV	DV	*b* and 95% CI	*t*	*p*
6.1	Description	Evaluation	0.234 [0.203, 0.266]	14.69	< .001
6.1	Serial position	Evaluation	-0.032 [-0.045, -0.019]	-4.76	< .001
6.1	Description * Position	Evaluation	-0.006 [-0.025, 0.013]	-0.63	.527
Description = Absent					
6.2	Serial position	Evaluation	-0.032 [-0.044, -0.020]	-5.16	< .001
Description = Present					
6.3	Serial position	Evaluation	-0.038 [-0.053, -0.023]	-4.88	< .001
6.4	Serial position	Distinctiveness	-0.052 [-0.069, -0.036]	-6.16	< .001
6.5	Serial position	Valence	0.010 [-0.005, 0.025]	1.35	.176
6.5	Distinctiveness	Valence	0.306 [0.291, 0.322]	38.42	< .001
6.6	Serial position	Evaluation	-0.031 [-0.045, -0.018]	-4.62	< .001
6.6	Distinctiveness	Evaluation	0.023 [0.009, 0.038]	3.12	.002
6.6	Valence	Evaluation	0.558 [0.543, 0.573]	73.34	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Discussion

Study 6 confirmed that the serial position-negativity effect extends to sequential evaluations of profile pictures. This finding is in line with previous research on the cognitive-ecological model which showed that sequential evaluations are primarily driven by features that differentiate targets from previously encountered ones (e.g., Alves et al., 2018). The present finding is however the first to confirm a central prediction from the model, namely that sequential differentiation leads to more negative evaluations of later-encountered targets when they are representatively sampled. Previous research had exclusively relied on manipulations of the valence of targets' shared and distinct attributes. In addition, we found that the serial position effect is not amplified when perceivers first describe the targets before evaluating them.

General Discussion

According to the cognitive-ecological model of social perception, evaluative biases towards individuals or groups can arise as innocent by-products of basic cognitive principles and the information ecology. In the present work, we derived a novel hypothesis from the model. We reasoned that the cognitive principle of differentiation, which prioritizes distinct information, should also apply more specifically to communication processes and serial person descriptions. Grice's maxims of effective communication (1975) require the avoidance of redundancies, which recommends differentiation. For example, the attribute "engineer" is not well-suited to describe an individual in a group of engineers. Instead, effective person descriptions must rely on distinct attributes that differentiate the individual from the general population or a given group or context. Crucially, negative attributes are overrepresented among people's distinct attributes because people have fewer negative than positive attributes, and negative attributes are more diverse than positive ones (Alves et al., 2017a; 2017b; 2018). Put differently, due to their high frequency and their low diversity, positive attributes are not well-suited to differentiate between individuals. Consequently, when perceivers describe several target persons sequentially, the differentiation principle forces them to avoid redundant person descriptions. We predicted that later-encountered target persons are described with increasingly distinct and therefore increasingly negative attributes.

We tested our predictions using a large set of representatively sampled Facebook profile pictures (all studies except Study 3) and videos of participants in the TV show The Bachelor (Study 3). In addition, we used subjective and more objective measures of our independent and dependent variables description distinctiveness and valence, and our findings converged. Finally, we preregistered our hypotheses and analyses and drew large samples of participants, ensuring sufficient statistical power. Therefore, we are confident in our findings' reproducibility, external and ecological validity, and generality.

Study 1 confirmed our model’s main predictions. Perceivers used mostly positive words to describe the first individual in a series of target person, consistent with the model’s assumed higher frequency of positive (vs. negative) attributes. However, descriptions of target persons became increasingly distinct and negative with increasing serial position of the target person, and distinctiveness statistically mediated the effect of serial position on valence.

Study 2 found that eliciting an assimilation goal eliminated the indirect effect from later to distinct to negative descriptions that we replicated in the control condition. Study 3 found that the indirect effect from later to distinct to negative descriptions generalizes to multi-sentence descriptions of target persons that appeared in short video clips.

Study 4 empirically confirmed a boundary condition of the serial position-negativity effect as predicted by our model. Specifically, the effect should be attenuated among overall negative target persons whose attributes are predominantly negative (instead of positive). Results showed that the serial position-negativity effect only occurred among predominantly positive target persons, where it was again accounted for by description distinctiveness. Among negative target persons, the effect was reversed, but description distinctiveness did not account for this. The latter finding suggests that in addition to the attenuation of the effect, additional forces resulted in a reversal of the effect among negative targets. We believe that shifting standards constitutes a viable explanation, but this needs to be verified by future research.

Studies 5a and 5b directly manipulated the distinctiveness of target persons, in addition to their overall valence. We created subsets of maximally distinct versus maximally similar positive versus negative target persons. In line with our model's prediction, the serial-position-negativity-effect occurred only among similar positive targets, where it once again was accounted for by description distinctiveness. The effect size in this condition was the largest of all studies, suggesting that the serial position-negativity effect may lead to particularly strong biases in situations where targets are not only positive but also similar to one another. This may for example be the case in job interviews where all applicants are highly qualified. As predicted, the effect did not occur among distinct positive targets, where perceivers did not run out of distinct positive attributes to describe the targets with. Also, in line with our model, we could elicit a reversed, serial position-positivity effect among similar negative targets, which was also accounted for by description distinctiveness. Again in line with our predictions, this effect did not occur among distinct negative targets.

The final Study 6 confirmed that the serial position-negativity effect is not confined to descriptions of targets but also applies to mere sequential evaluations. While previous research has already reported such evaluative disadvantages of later-encountered attitude objects (e.g., Alves et al., 2018, 2020), Study 6 was the first to confirm this phenomenon with representatively sampled picture stimuli. Study 6 also found that the magnitude of the serial position-negativity effect in evaluations is similar regardless of whether participants describe the targets prior to evaluating them or not.

Theoretical Advancement and Practical Implications

Our findings are the first that empirically support the cognitive-ecological model of social perception with representatively sampled, real-world stimuli that people actually and frequently encounter on social media platforms or when watching TV. Previous research relied on rather fictional alien cartoons or brand logos (e.g., Alves et al., 2018; 2020). Second, our findings are the first to confirm that the cognitive principle of differentiation applies to communication processes and serial person descriptions more specifically. Previous research was confined to attitude and choice formation, and learning / memory (e.g., Alves et al., 2018; 2020).

Third, the present findings establish a novel phenomenon: the serial position-negativity effect in person description. While the effect logically follows from the cognitive-ecological model, we believe that the effect and its explanation is not obvious to most people. At the same time, the effect's practical implications are quite straightforward. Whenever social perceivers describe other individuals they encounter sequentially, earlier-encountered individuals will be described more favorably. Note that there are many comparative settings such as job interviews, art, music, and sports performances, or online dating platforms, where perceivers encounter series of target persons and discuss their impressions with their peers, often to arrive at consequential decisions such as who gets hired etc.

Our findings may also contribute to well-known evaluative biases in social perception. For example, suppose people tend to describe later-encountered individuals or groups based on their distinct attributes that differentiate them from more familiar individuals and groups. This may give rise to the formation of negative stereotypes towards strangers, or members of out-groups. When people meet a new colleague, or encounter members of unfamiliar groups such as refugees, and if they rely on distinct attributes to label them, we can expect that emerging impressions are likely negative, contributing to typical interpersonal or intergroup biases. These speculations do however hinge on the assumption that differentiation does not only operate locally within a given learning context but also more globally. Note that in our studies, participants differentiated later-encountered targets from earlier-encountered targets within the same learning context. If people also differentiate novel individuals or groups from more long-term, global standards such as their in-groups, we can expect typical intergroup biases to occur that traverse single learning contexts and that may give rise to the formation of negative stereotypes towards out-groups.

Considering that people are most familiar with themselves, the differentiation principle may even contribute to forming self-superiority effects. Assuming that people will describe other people based on attributes they themselves do not have, descriptions of the self will naturally be more positive than those of others.

Open Questions

Person variables may moderate the serial position negativity-effect. Future research could test whether people who are more inclined to seek novelty/sensation (vs. routine/comfort; Pearson, 1970) show a greater bias towards others they encounter later in a series.

Situational variables may also moderate the effect. Participants in our experiments were simply instructed to describe their impressions of target persons. Suppose people are instructed to form preferences to decide whom to hire or whom to ask out for a date. In that case, they may feel an even stronger urge to differentiate them, which should amplify the serial position-negativity effect. Another possibility is that the differentiation motive is amplified when perceivers' task is to later recognize the targets they will encounter, or when their descriptions serve for others to identify certain targets (e.g., eyewitness testimony). In such situations, it may be especially beneficial to rely on differentiating attributes, too.

Future research may also identify contexts where perceivers rely on shared attributes instead of distinct ones. For example, it could be that perceivers describe individuals who are members of the same group based on their shared attributes, especially when encountering members of other groups. A series of members of the same group may actually be described with primarily positive attributes, giving rise to increasingly favorable impressions. If confirmed, this mechanism could contribute to explaining the effect that a group of individuals is rated as more attractive than when their members are individually rated in a sequence (Walker & Vul, 2014).

Another open question is whether the differentiation principle would render descriptions of the same target person more negative. If perceivers describe more and more distinct attributes of a target they encounter repeatedly, their descriptions and overall evaluation of that target may become more negative. This would be in line with the “less-is-more-effect” (Norton et al., 2007), according to which person impressions become more negative with an increasing amount of person-related information that is sampled (but see Ullrich et al., 2013).

At this point, we do not know how series length influences the serial position-negativity effect. It seems reasonable to assume that the effect fades out after a certain number of trials, simply because perceivers will forget which descriptors they have already used. Across our six studies, we see that the serial position effect is often strongest between the first and the second target and then somewhat wears off. Additional analyses provided in the supplementary materials (Table 9) do however show that if the first target is removed from Study 1, the base serial position effect is still significant, and this is also the case in many of the subsequent studies. Nevertheless, the serial position effect is likely negatively accelerated and may eventually reach a bottom. Future research could further investigate the dynamics of the serial position effect over longer sequences of target descriptions.

Finally, the situational features that reset the differentiation principle and the serial position-negativity effect remain to be identified. Of course, people's descriptions of others do not become more negative forever, but likely reset when a new context is identified. Such context changes could be initiated by a change in place or time. For example, longer temporal intervals between serially-encountered individuals may lower the likelihood that these will be differentiated from one another. Distractions could have the similar context-breaking effects.

Conclusion

When perceivers serially describe target persons, they rely on distinct attributes that differentiate a given individual from earlier-encountered ones. Because negative attributes are overrepresented among distinct attributes, person descriptions become increasingly negative with increasing serial position of the encountered target persons. These negatively biased descriptions of novel or recently-encountered individuals may contribute to several well-known biases in social perception, including the formation of negative impressions, prejudice and stereotypes towards strangers, or members of out-groups or minorities such as immigrants.

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Supplementary Materials

Table 1

Supplemental analyses in Study 1

M	IV	DV	*b* and 95% CI	*t*	*p*
Distinctiveness = raw (not log-transformed); Valence = database					
1.4	Serial Position	Valence	-0.018 [-0.030, -0.005]	-2.79	.005
1.5	Serial Position	Distinctiveness	-0.053 [-0.067, -0.040]	-7.86	< .001
1.6	Serial Position	Valence	0.004 [-0.007, 0.016]	0.75	.454
1.6	Distinctiveness	Valence	0.300 [0.288, 0.312]	48.33	< .001
Distinctiveness = universal (not situational); Valence = database					
1.7	Serial Position	Valence	-0.018 [-0.030, -0.005]	-2.79	.005
1.8	Serial Position	Distinctiveness	-0.035 [-0.049, -0.021]	-4.90	< .001
1.9	Serial Position	Valence	-0.009 [-0.021, 0.004]	-1.40	0.160
1.9	Distinctiveness	Valence	0.237 [0.224, 0.250]	36.55	< .001
Distinctiveness = subjective (not objective); Valence = describers (not database)					
1.10	Serial Position	Valence	-0.007 [-0.019, 0.005]	-1.18	0.240
1.11	Serial Position	Distinctiveness	-0.036 [-0.049, -0.023]	-5.35	< .001
1.12	Serial Position	Valence	0.003 [-0.009, 0.014]	0.44	.662
1.12	Distinctiveness	Valence	0.265 [0.253, 0.277]	42.93	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 2

Supplemental analyses in Study 2; Valence = database

M	IV	DV	*b* and 95% CI	*t*	*p*
Goal = Control					
2.9	Aversiveness	Valence	-0.089 [-0.104, -0.074]	-11.47	< .001
2.9	Serial position	Valence	-0.012 [-0.021, -0.004]	-2.87	.004
2.9	Aversiveness * Position	Valence	0.012 [0.004, 0.021]	2.89	.004
Goal = Assimilation					
2.10	Aversiveness	Valence	-0.079 [-0.100, -0.059]	-7.64	< .001
2.10	Serial position	Valence	0.007 [-0.001, 0.015]	1.68	.092
2.10	Aversiveness * Position	Valence	-0.004 [-0.013, 0.004]	-1.04	.300

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate;

95% CI = 95% confidence interval [lower bound, upper bound].

Table 3

Supplemental analyses in Study 3

M	IV	DV	*b* and 95% CI	*t*	*p*
Distinctiveness = universal (not situational)					
3.4	Serial Position	Valence	-0.034 [-0.052, -0.016]	-3.68	< .001
3.5	Serial Position	Distinctiveness	0.029 [0.011, 0.047]	3.13	.002
3.6	Serial Position	Valence	-0.031 [-0.051, -0.012]	-3.14	.002
3.6	Distinctiveness	Valence	0.029 [0.009, 0.049]	2.84	.004
Valence = global (not local [i.e., word by word])					
3.7	Serial Position	Valence	-0.022 [-0.040, -0.004]	-2.42	.015
3.8	Serial Position	Distinctiveness	-0.052 [-0.067, -0.037]	-6.72	< .001
3.9	Serial Position	Valence	-0.012 [-0.030, 0.006]	-1.31	.190
3.9	Distinctiveness	Valence	0.153 [0.135, 0.171]	16.62	< .001
Valence = database					
3.10	Aversiveness	Valence	-0.166 [-0.199, -0.134]	-9.99	< .001
3.10	Serial position	Valence	-0.034 [-0.052, -0.016]	-3.68	< .001
3.10	Aversiveness * Position	Valence	0.001 [-0.017, 0.019]	0.09	.925

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 4

Supplemental analyses in Study 4; Distinctiveness = subjective (not objective); Valence = describers (not database)

M	IV	DV	*b* and 95% CI	*t*	*p*
4.9	Target Valence	Valence	-0.917 [-1.006, -0.828]	-20.19	< .001
4.9	Serial Position	Valence	-0.020 [-0.035, -0.004]	-2.41	.016
4.9	Target Valence * Position	Valence	0.066 [0.044, 0.089]	5.83	< .001
4.10	Target Valence	Distinctiveness	-0.333 [-0.413, -0.253]	-8.15	< .001
4.10	Serial Position	Distinctiveness	-0.069 [-0.088, -0.050]	-7.22	< .001
4.10	Target Valence * Position	Distinctiveness	0.060 [0.033, 0.086]	4.46	< .001
Target Valence = Positive people					
4.11	Serial Position	Valence	-0.027 [-0.045, -0.009]	-2.95	.003
4.12	Serial Position	Distinctiveness	-0.067 [-0.086, -0.048]	-7.03	< .001
4.13	Serial Position	Valence	-0.005 [-0.022, 0.012]	-0.61	.539
4.13	Distinctiveness	Valence	0.308 [0.291, 0.326]	34.30	< .001
Target Valence = Negative people					
4.14	Serial Position	Valence	0.051 [0.033, 0.070]	5.56	< .001
4.15	Serial Position	Distinctiveness	-0.006 [-0.024, 0.013]	-0.57	.569
4.16	Serial Position	Valence	0.046 [0.029, 0.063]	5.31	< .001
4.16	Distinctiveness	Valence	0.224 [0.206, 0.241]	25.01	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 5a

Supplemental analyses in Study 5a; Distinctiveness = subjective (not objective);

Valence = describers (not database)

M	IV	DV	*b* and 95% CI	*t*	*p*
5a.9	Similarity	Valence	-0.045 [-0.244, 0.154]	-0.44	.661
5a.9	Serial Position	Valence	0.004 [-0.021, 0.030]	0.35	.728
5a.9	Similarity * Position	Valence	-0.085 [-0.121, -0.050]	-4.71	< .001
5a.10	Similarity	Distinctiveness	0.045 [-0.192, 0.282]	0.37	.714
5a.10	Serial Position	Distinctiveness	-0.019 [-0.045, 0.007]	-1.42	.157
5a.10	Similarity * Position	Distinctiveness	-0.095 [-0.132, -0.059]	-5.09	< .001
Similarity = Low					
5a.11	Serial Position	Valence	0.006 [-0.019, 0.031]	0.47	.635
5a.12	Serial Position	Distinctiveness	-0.019 [-0.045, 0.007]	-1.45	.146
5a.13	Serial Position	Valence	0.012 [-0.013, 0.036]	0.93	.351
5a.13	Distinctiveness	Valence	0.242 [0.215, 0.268]	17.85	< .001
Similarity = High					
5a.14	Serial Position	Valence	-0.119 [-0.145, -0.094]	-9.19	< .001
5a.15	Serial Position	Distinctiveness	-0.112 [-0.138, -0.086]	-8.42	< .001
5a.16	Serial Position	Valence	-0.045 [-0.070, -0.021]	-3.64	< .001
5a.16	Distinctiveness	Valence	0.249 [0.224, 0.273]	19.75	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 5b

Supplemental analyses in Study 5b; Distinctiveness = subjective (not objective);

Valence = describers (not database)

M	IV	DV	*b* and 95% CI	*t*	*p*
5b.9	Similarity	Valence	0.347 [-0.026, 0.719]	1.82	.084
5b.9	Serial Position	Valence	0.003 [-0.021, 0.026]	0.23	.821
5b.9	Similarity * Position	Valence	0.058 [0.025, 0.091]	3.44	< .001
5b.10	Similarity	Distinctiveness	0.177 [-0.046, 0.400]	1.55	.136
5b.10	Serial Position	Distinctiveness	-0.003 [-0.029, 0.023]	-0.24	.807
5b.10	Similarity * Position	Distinctiveness	-0.060 [-0.096, -0.023]	-3.19	< .001
Similarity = Low					
5b.11	Serial Position	Valence	-0.001 [-0.024, 0.023]	-0.06	.955
5b.12	Serial Position	Distinctiveness	-0.003 [-0.029, 0.023]	-0.24	.808
5b.13	Serial Position	Valence	-0.001 [-0.024, 0.022]	-0.07	.942
5b.13	Distinctiveness	Valence	0.131 [0.107, 0.156]	10.66	< .001
Similarity = High					
5b.14	Serial Position	Valence	0.104 [0.079, 0.129]	8.14	< .001
5b.15	Serial Position	Distinctiveness	-0.069 [-0.095, -0.043]	-5.22	< .001
5b.16	Serial Position	Valence	0.079 [0.055, 0.103]	6.53	< .001
5b.16	Distinctiveness	Valence	0.210 [0.186, 0.234]	17.04	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 6

Supplemental analyses of the valence of the first person description that perceivers provided

S	C	V	*M* and 95% CI	*t*	*p*
1		Database	6.193 [6.084, 6.302]	21.48	< .001
1		Describers	5.132 [5.035, 5.228]	22.96	< .001
2	Control	Database	6.237 [6.159, 6.316]	31.01	< .001
2	Assimilate	Database	6.364 [6.287, 6.441]	34.76	< .001
3		Database	6.127 [6.103, 6.151]	91.84	< .001
4	Positive	Database	7.219 [7.113, 7.325]	41.00	< .001
4	Positive	Describers	5.947 [5.856, 6.038]	41.83	< .001
4	Negative	Database	4.702 [4.552, 4.853]	-3.87	< .001
4	Negative	Describers	3.836 [3.703, 3.969]	-2.42	.016
5a	Dissimilar	Database	7.008 [6.892, 7.123]	34.01	< .001
5a	Dissimilar	Describers	5.852 [5.742, 5.963]	32.82	< .001
5a	Similar	Database	7.356 [7.259, 7.452]	47.72	< .001
5a	Similar	Describers	6.168 [6.075, 6.260]	45.70	< .001
5b	Dissimilar	Database	4.508 [4.366, 4.650]	-6.80	< .001
5b	Dissimilar	Describers	3.675 [3.534, 3.817]	-4.50	< .001
5b	Similar	Database	4.553 [4.411, 4.695]	-6.17	< .001
5b	Similar	Describers	4.061 [3.942, 4.180]	1.00	.318
6	Description	Database	6.188 [6.122, 6.254]	35.22	< .001

Note. S = Study; C = condition (if applicable); V = valence measure (database by Warriner and colleagues, 2013, or describers in the present research); *M* = mean rating tested against the midpoint of the scale (5 on a 1-9 scale [V = database] or 4 on a 1-7 scale [V = describers]); 95% CI = 95% confidence interval [lower bound, upper bound]. Perceivers did not rate the valence of their descriptions of the target persons in Studies 2 and 3; hence, Table 7 shows no data for valence as rated by the describers in Studies 2 and 3.

Table 7

Supplemental analyses of the distinctiveness of the person description that perceivers provided

S	C	*M* and 95% CI
1		88.7% [87.8%, 89.5%]
2	Control	88.3% [87.6%, 89.0%]
2	Assimilate	41.5% [40.6%, 42.5%]
4	Positive	85.4% [83.9%, 86.9%]
4	Negative	89.0% [87.8%, 90.1%]
5a	Dissimilar	96.4% [95.7%, 97.1%]
5a	Similar	90.0% [88.6%, 91.5%]
5b	Dissimilar	95.6% [94.8%, 96.4%]
5b	Similar	89.8% [88.4%, 91.1%]
6	Description	97.4% [97.1%, 97.8%]

Note. S = Study; C = condition (if applicable); *M* = mean rate of distinct, unique descriptions; 95% CI = 95% confidence interval [lower bound, upper bound]; there is no data for Study 3 because in that study perceivers used several sentences to describe the target persons, rendering each description like no other, and thus meaninglessly 100.0% [100.0%, 100.0%].

Table 8

Simulation presented in Study 1

M	IV	DV	*b* and 95% CI	*t*	*p*
9.1	Serial position	Valence	-0.080 [-0.084, -0.076]	-36.22	< .001
9.2	Serial position	Distinctiveness	-0.080 [-0.084, -0.076]	-36.22	< .001
9.3	Serial position	Valence	0.000 [0.000, 0.000]	-1.15	.247
9.3	Distinctiveness	Valence	0.999 [0.999, 1.000]	16485.681	< .001

Note. M = Model; IV and DV = independent and dependent variable; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound]. Lower values on the distinctiveness measure indicate higher distinctiveness.

Table 9

Supplemental analyses excluding the first target person in each condition of each study

S	C	IV	DV	NT	*M* and 95% CI	*t*	*p*
1		Serial position	Valence	19	-0.016 [-0.030, -0.003]	-2.41	.016
2	Control	Serial position	Valence	19	-0.007 [-0.016, 0.003]	-1.40	.162
2	Assimilate	Serial position	Valence	19	0.007 [-0.002, 0.016]	1.54	.123
3		Serial position	Valence	9	-0.020 [-0.041, 0.001]	-1.85	.064
4	Positive	Serial position	Valence	19	-0.032 [-0.052, -0.012]	-3.11	.002
4	Negative	Serial position	Valence	19	0.038 [0.018, 0.057]	3.78	< .001
5a	Dissimilar	Serial position	Valence	9	-0.003 [-0.034, 0.028]	-0.21	.833
5a	Similar	Serial position	Valence	9	-0.071 [-0.101, -0.040]	-4.59	< .001
5b	Dissimilar	Serial position	Valence	9	0.005 [-0.025, 0.035]	0.35	.728
5b	Similar	Serial position	Valence	9	0.064 [0.035, 0.094]	4.26	< .001
6	Evaluation	Serial position	Evaluation	4	-0.004 [-0.021, 0.013]	-0.43	.670
6	Description	Serial position	Evaluation	4	-0.009 [-0.030, 0.013]	-0.77	.440

Note. S = Study; C = condition (if applicable); IV and DV = independent and dependent variable; NT = number of targets after excluding the first target; *b* = estimate; 95% CI = 95% confidence interval [lower bound, upper bound].

Table 10

List of helper words excluded from the measurement of distinctiveness and valence in Study 3

a, an, with, he, she, is, seems, looks, in, on, its, that, this, for, but, so, or, my, his, her, about, across, likes, their, they, them, they're, she's, he's we, I, you, your, hers, that's, it's into, has, having, had, takes, own, through, as, was