Measuring the Impact of Multiple Social Cues to Drive Theoretical Advancement in Person Perception Research

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Abstract

Forming impressions of others is a fundamental aspect of social life and one of the foundational questions of social psychology. These impressions necessitate the integration of many and varied sources of information about other people, including social group memberships, apparent personality traits, inferences from observed behaviors, etc. However, methodological limitations have hampered progress in understanding this integration process. In particular, extant approaches have been unable to measure the independent contributions of multiple features to a given impression. In this article, we describe those limitations and their impact on developing and testing competing theoretical accounts of person perception. We promote a solution based on a computational modeling approach, describe the MCI multinomial processing tree model of person perception, and provide empirical demonstrations of how application of the model can resolve long-standing debates among person perception researchers. Finally, we survey a variety of questions to which this approach can be profitably applied.

Keywords: person perception; impression formation; multinomial processing trees; computational modeling; stereotyping

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Forming judgments of other people is one of the most basic and consequential elements of social life, impacting virtually every interpersonal and intergroup interaction. Accordingly, the study of impression formation has occupied a central role in the field of social psychology since its inception. From the publication of Asch's seminal work (1946), perhaps the most fundamental objective has been to understand how people combine the implications of multiple and varied attributes in judging others (see also Anderson, 1968). Cues relating to social group membership (e.g., racial appearance), personality traits (e.g., trustworthiness), emotions (e.g., anger), witnessed behaviors (e.g., an act of violence), and many other attributes may be relied upon in forming a coherent impression. Though many influential models have been proposed to account for this complex task, testing them has been hindered by measurement limitations. In turn, these limitations have significantly slowed theoretical progress. The aim of this paper is to describe current challenges to theory testing and advancement, and to offer a solution, via computational modeling. We show how a computational model circumvents current limitations and how it can be used to directly test and compare a plethora of person perception models.

Theoretical Background

Many prominent models of person perception posit that the use of different features is a competitive process, such that relying more on one feature implies relying less on others. We refer to this as the *inverse relativity* assumption. For example, in their initial presentations, both Brewer's (1988; 2014; see also Brewer & Feinstein, 1999) and Fiske and Neuberg's (1990; see also Fiske et al., 1999) influential models propose an inverse relationship between the use of social category (e.g., group stereotypes) and individuating (e.g. individual behavior) information:

Increased stereotyping requires decreased individuation and vice versa. So, for example, if cognitive load is predicted to reduce the reliance on individuating behaviors, it should also increase the use of social stereotypes (e.g., Fiske & Neuberg, 1990). More recent models similarly invoke inverse relativity. Consider Petsko and colleagues' (2022) Lens Model, which proposes that people use a variety of contextually activated lenses in perceiving others. According to the model, once one social category lens (e.g., race: Black) has been activated, the use of other categories is necessarily diminished.

Beyond the inverse relativity assumption, many of these models make predictions about which features are prioritized, and when, during person perception. Specifically, they propose that category-based information such as stereotypes (which distinguish social groups from one another) impact judgments more than individuating features (which distinguish one individual from others). Because category-based features are thought to be inferred and applied more easily than other features, their advantage is magnified when perceivers lack either the motivation or ability to attend carefully to others (Brewer, 1988; Fiske & Neuberg, 1990).

Of course, an inverse relationship among attributes is only one of many possible patterns of feature integration. In principle, variations in the use of one feature may be uncorrelated or positively correlated with the use of other cues. For example, the Social Judgeability Model (SJM; Leyens et al., 1992; Yzerbyt et al., 1994; 1998) predicts that stereotyping is more likely when individuating features are available, as those individuating features provide perceivers with the subjective sense of being fair and decrease concerns with unfairly stereotyping a target (Darley & Gross, 1983; Norton et al., 2004; Yzerbyt et al., 1994).

A class of network models (e.g., Freeman & Ambady, 2011; Kunda & Thagard, 1996) also eschews the inverse relativity assumption, assuming that all available information may be integrated, as in early models of impression formation (e.g., Asch, 1946; Andersen, 1968), and that the use of different features may be positively correlated, negatively correlated, or not correlated at all (Freeman et al., 2012). Rather, patterns of feature integration may vary as a function of target-level, perceiver-level, and situational variables. This latter point is both a strength and a weakness of these models: They are flexible enough to account for almost any pattern of feature integration but do not make sufficiently precise predictions to be falsifiable as a general model of person perception, though some specific hypotheses may be testable (e.g., Freeman et al., 2012; for a more detailed discussion, see Petsko & Bodenhausen, 2020). For example, these models imply that cues processed earlier during person perception have more time and opportunity to influence final judgments. However, there is no claim as to which features, and when, are going to be detected earlier than others.

Measurement Problems

Though there are a plethora of excellent models of person perception making competing predictions, measurement limitations have presented a significant barrier to conducting clear tests of their claims and to arbitrate among them. Specifically, clear tests of the models require the ability to measure the independent influences of multiple features on impressions and their theoretically proposed relationships (e.g., race dominating impressions over behavior).

To illustrate the problem, consider an archetypal study that attempts to assess the extent to which different types of information influence judgments along some stereotype-relevant dimension (e.g., How threatening is Bob?). Those judgments, in and of themselves, cannot provide independent estimates of the impacts of social stereotypes (Bob is Black and therefore stereotypically threatening), Bob’s somewhat threatening behavior, and Bob’s happy facial expression. In this case, a relatively stereotypic judgment of Bob as threatening may result from increased stereotyping, increased influence of his behavior, decreased impact of his facial expression, or all three. In turn, a relatively counter-stereotypic judgment may result from decreased stereotyping, decreased use of the behavior, increased use of the expression, or all three.

For the sake of further illustration, consider the classic finding that people tend to make more stereotypic judgments of suspects' alleged misbehavior when they are tested at the low point versus high point of their circadian cycles (Bodenhausen, 1990). This is the sort of evidence that has been seen as supporting prominent dual-process models that include inverse-relativity assumptions: People make more stereotypic judgments when they have diminished processing capacity and motivation. However, though a fascinating and important illustration, the extent to which different information contributes to the effect is unclear. Does the increase in stereotyping reflect the greater use of category information, the diminished use of other relevant details about the targets, or both? Alternatively, it may be that both features are relied upon more or less, but that the change in one is greater than the other. It is impossible to say.

As another example, consider the finding that those with greater implicit bias are quicker to recognize happiness in White faces and anger in Black faces (Hugenburg & Bodenhausen, 2003). In this research, the expressions of Black and White faces slowly changed from angry to happy or from happy to angry, and participants were tasked with indicating when the expression had changed. Those with greater implicit bias judged the onset of happiness in White faces and anger in Black faces to occur relatively quickly. Though an important demonstration of the effects of stereotypes on emotion perception, the extent to which different types of information contribute to the effect is unclear. Does construing Black faces quickly becoming angry reflect greater use of race, less use of facial expression or some combination of changes in both? Again, it is impossible to say.

As a final illustration, consider the use of mouse-tracking to capture the parallel activation of and conflict among different types of information. Mouse-tracking tasks instruct participants to move their cursor from a fixed starting position toward one of two (or more) response options based on the target stimulus provided. A participant might be instructed, for example, to move their cursor to the top left corner of their screens if the face is Black (versus White). The extent to which the cursor initially moves toward one response before being tracked to the other response indicates the extent of conflict between the two response options and that both have been activated in parallel (e.g., Hehman et al. 2015; Stillerman & Freeman, 2019). This is the kind of evidence that is seen as supporting *integration* models of person perception: Clearly, multiple cues are simultaneously pushing and pulling responses in different directions.

However, although mouse-tracking measures are excellent indicators of parallel activation and response conflict, they cannot independently assess the extents to which the two different options are influencing cursor movement (Stillman et al., 2018). For example, when used to assess race categorization, participants show a stronger initial tendency to move the cursor toward White categorizations when an ambiguously Black target is wearing a suit versus a janitor’s uniform (Freeman & Ambady, 2009). This measure of conflict between White and Black response options is interpreted to reflect an initially greater impact of clothing features at the expense of race features before a transition to greater impact of race features at the expense of clothing features. However, the influence of the features cannot be measured independently. Movement toward one option may reflect increased influence of that option, decreased influence of the other option, or some combination of changes in both. The measures are inherently relative and pit use of the two cues against one another in an inverse fashion.

Computational Modeling of Person Perception with a Multinomial Processing Tree

Here, we describe a solution to the problem of specifying the contributions of multiple features underlying person perception. Namely, we propose to apply computational modeling to this problem in the form of a multinomial processing tree (MPT). MPTs are measurement models comprised of a set of equations that can predict when and how judgments are made (for reviews, see Batchelder & Riefer, 1999; Calanchini et al., 2018; Erdfelder et al., 2009; Hütter & Klauer, 2016; Sherman et al., 2010). Each unique response in a task (e.g., correctly categorizing a Black face as Black) is assigned an equation that reflects the probability of its occurrence. The MPT equations reflect the impact of a set of processing parameters thought to influence judgments and the manner in which they are thought to relate to one another. Each parameter reflects a distinct component of the judgments (e.g., use of race information). The parameters are estimated by entering the frequencies of participants' actual responses as outcomes in the equations, and their values reflect the probability that their respective processing component contributes toward the observed responses. Each estimated parameter can vary independently of all others, yielding distinct estimates for the relative contributions of each component. The application of MPTs has already proven useful for identifying and measuring the cognitive *processes* underlying a wide variety of social judgments (e.g., Heycke & Gawronski, 2020; Krieglmeyer & Sherman, 2012; Klauer & Wegner, 1998; Payne et al., 2010). Here, we promote the use of an MPT for identifying and measuring the contributions of different *content* to social judgments (e.g., cues to social group membership, emotion, personality traits, behavior, etc.).

Application of the Multi-Cue Integration Model

Here, we describe the Multi-Cue Integration (MCI) model, an MPT for use in person perception research and provide an empirical example to illustrate its benefits. In this experiment, participants were directed to judge targets by their gender appearance (man, woman). Target faces varied not only on sex cues, a task-relevant dimension, but also emotional expression, a task-irrelevant dimension. To investigate how a feature's signal strength affects its use, we further manipulated the stimuli by morphing them orthogonally across the two dimensions. For example, angry faces were morphed with happy faces to create weaker signal strength for angry expressions (i.e., happier-looking angry face) and happy expressions (i.e., angrier-looking happy faces). Therefore, faces were either strong or weak in each of the orthogonally manipulated features. Theories proposing inverse relativity between the use of different features predict a negative correlation between the use of sex and expression cues. By contrast, from a social judgeability perspective (Leyens et al., 1992; Yzerbyt et al., 1994) or various network model perspectives, the use of gender and expression cues may be positively correlated or uncorrelated (Becker et al., 2007; Freeman et al., 2012; Hess et al., 2004; Hess et al., 2009; Hess et al., 2010).

We entered participants' responses into an MPT model that estimates the probability with which each feature contributes to judgments about a person. The model estimates parameters for the use of sex cues (C_1) and emotion cues (C_2), but the model could be amenable to any other pair of cues (e.g., race and age cues). The model also includes a parameter to account for a response bias (G) participants may hold (e.g., tendency to judge others as women under uncertainty). To further describe the MPT in this current example, we point to Figure 1, which illustrates the processing tree and the unique responses assigned to various paths along the tree. For example, following along in the figure, the MPT predicts a probability of correctly categorizing a happy male face by the joint contributions of relying on sex cues [C_1] and a tendency to categorize others as men in the absence of detecting sex and emotion cues [$(1- C_1) \times (1- C_2) \times (1-G)$] – that is, a response bias toward *man*. The compliment of that probability, the probability of incorrectly categorizing a happy male target, is predicted by the joint probability [$(1- C_1) \times C_2 + (1- C_1) \times (1- C_2) \times G$]. Therefore, by simply following the paths along the tree, the equations predicting each unique response can be derived.[1]

Those equations predict the proportions of responses in the observed dataset. A model fit estimate is computed for the difference between the predicted and observed responses. In this way, the model can be tested for its ability to predict the observed data, which was adequate for these example data (Median Individual $T_{1\ p\text{-}value} = .53$, Aggregate $T_{1\ p\text{-}value} = .03$, Aggregate $T_{2\ p\text{-}value} = .07$). More importantly, model fit indices provide a mechanism for testing competing person perception theories.[2]

[1] More detailed discussions of the mechanics of using MPTs is beyond the scope of this text. We recommend general (e.g., Schmidt et al., 2022) and software-specific (e.g., Hartmann et al., 2020; Heck et al., 2018; Moshagen, 2010; Stahl & Klauer, 2007; Singmann & Kellen, 2013) tutorials for instructions on developing and applying MPTs.
[2] More technical details regarding the estimation and comparison of MPT parameters also are beyond the scope of this paper's main text. Those details are openly available in the Supplementary Materials (https://osf.io/gxbc5/).

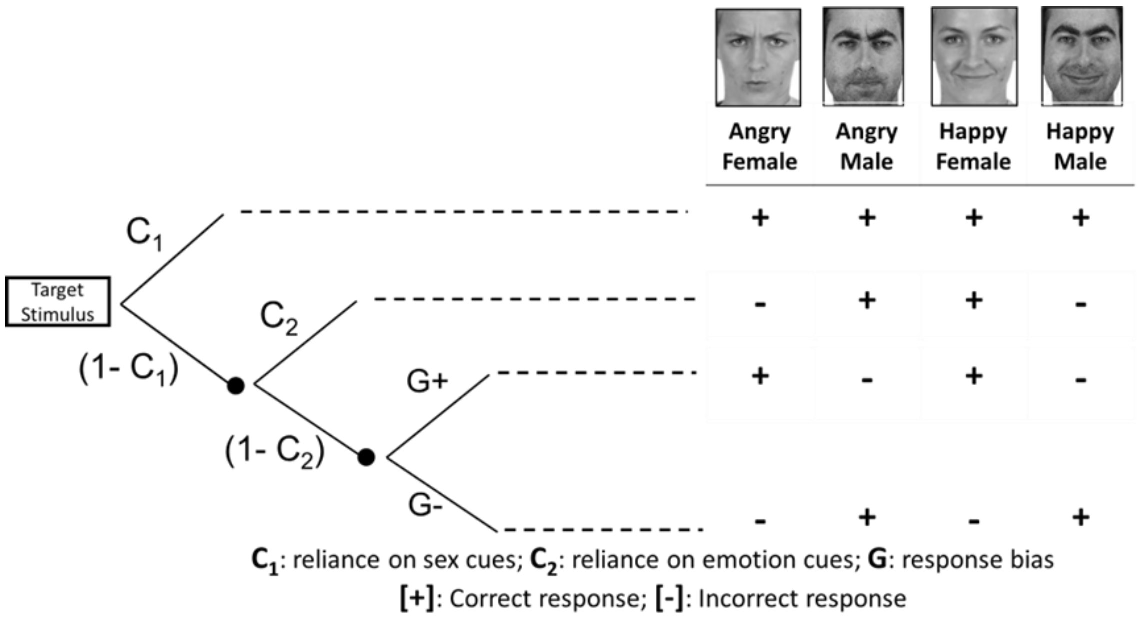

Figure 1. Diagram of the MCI model used to measure person perception data from a paradigm in which judgments were made of targets varying in sex and emotion cues. The manifest outcome is represented on the right side of the figure (i.e., binary responses about the person's gender). The paths along the tree depict the processing paths assumed by the model to explain responses for each trial type.

The experimental manipulations of signal strength for each source of information substantially affected the use of its respective feature: Weaker signal in sex cues decreased the use of sex cues (Figure 2) and weaker signal in expression cues decreased the use of expression cues (Figure 3). However, signal strength of emotion cues did not affect the use of relevant sex cues and signal strength of sex cues did not affect the use of emotion cues. That is, signal strength had selective influence on its respective feature.

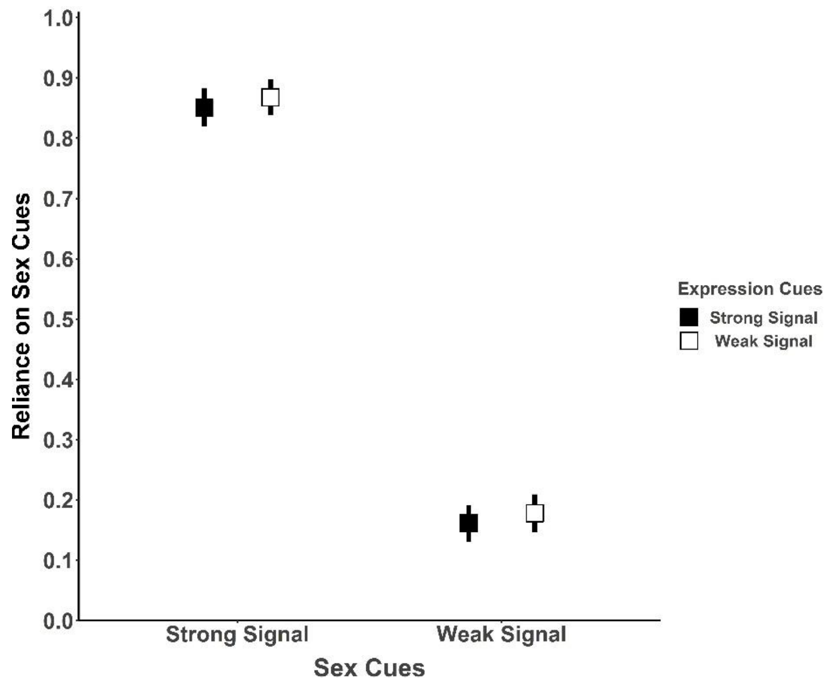

Figure 2. Plot of mean-level estimate for the reliance on sex cues to form gender categorizations. The x-axis reflects the strength in signal of relevant sex cues, and the color of the points reflects the strength in signal of irrelevant expression cues. The y-axis reflects the mean-level probability estimate of relying on sex cues. Error bars signify 95% Bayesian credibility intervals around the estimate.

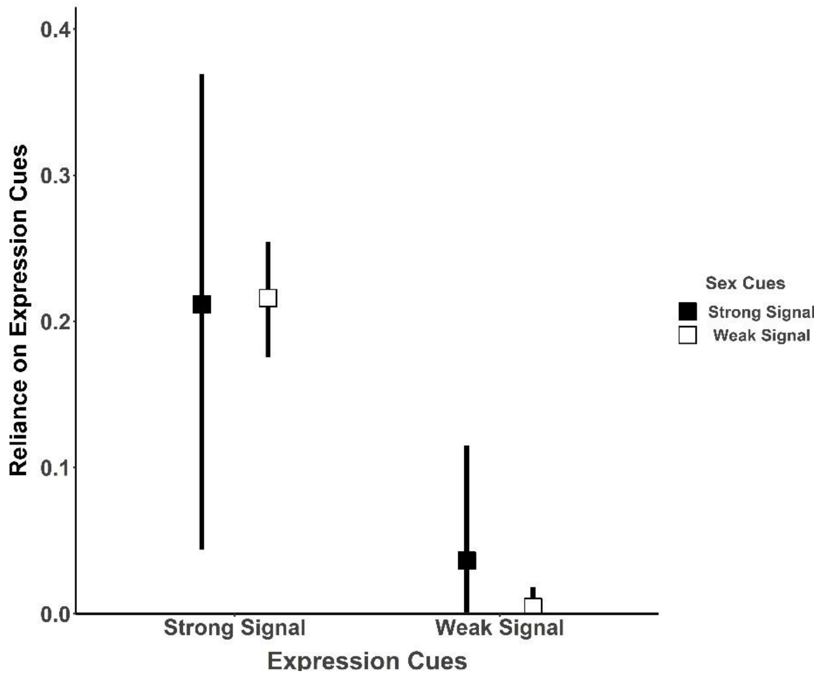

Figure 3. Plot of mean-level estimate for reliance on expression cues to form gender categorizations. The x-axis reflects the strength in signal of relevant sex cues, and the color of the points reflects the strength in signal of irrelevant expression cues. The y-axis reflects the mean-level probability estimate of relying on expression cues. Error bars signify 95% Bayesian credibility intervals around the estimate.

We also examined the correlation between use of the two cues and observed that when neither cue was manipulated by morphing (i.e., stronger signal strength), a credible, strong, and positive correlation emerged between the C_1 and C_2 parameters, $r = .64$, $BCI_{95\%}$ [.29,.92]. When at least one cue was weaker in signal strength, no credible correlation emerged (for reported statistics, see Supplementary Materials).

To test whether sex or expression cues dominated these judgments, we refit the data to a model that conditionally prioritized expression over sex information (i.e., we assigned expression cues to the C_1 parameter and sex cues to the C_2 parameter) and compared their DIC absolute fit indices. Comparison of the two models yielded a $\Delta_{DIC} = 1.81$, indicative of extremely weak evidence (Burnham & Anderson, 2002) and, therefore, no clear support for one model over the other.

Summary

The results of this empirical example showcase the importance of distinguishing the extents to which multiple features underly person perception and the usefulness of the MCI model for doing so. By measuring the independent contributions of different features, we were able to directly test key predictions of impression formation models. Whereas the inverse relativity assumption of dual-process or lens models suggests that increased use of sex cues should be concomitant with decreased use of expression cues, and vice versa, no such pattern emerged. By contrast, the modest evidence for a positive association in use of sex and expression cues is more consistent with a social judgeability or network model approach. However, at the same time, the fact that the diagnosticity of each cue did not affect the use of the other cue is inconsistent with these models. Stronger signal in sex or expression cues increased use of those features but had no impact on the use of the other cue. Finally, the lack of clear evidence favoring either a sex-dominant or expression-dominant model as the better explanation of the data also counters models expecting social categories to dominate social judgments. This is especially notable, given that the task explicitly required judgments of gender, a category more associated with sex than emotion.

Further Applications of the MCI Model

The MCI model offers a highly flexible solution for testing key questions and theories surrounding person perception that can be applied to any task in which judges must select among discrete options (e.g., IAT, priming, memory, mouse-tracking, etc.).

Operating Conditions of Person Perception

Prominent models of person perception commonly assume that information pertaining to social categories is more efficiently processed and applied than other information (e.g., individuating behaviors). As such, these models predict greater impact of social categories and lesser impact of individuating traits and behaviors, especially when perceivers have limited processing capacity (e.g., Brewer, 1988; Fiske & Neuberg, 1990). The supposed efficiency of activation and application of social category stereotypes implies that their processing should be unaffected or even increased when the perceiver is under cognitive load or time pressure, for example. Individuating traits and behaviors, on the other hand, are assumed to be applied less fully under those same conditions (e.g., Sherman et al., 2000; Swencionis & Fiske, 2013).

Those same theoretical models of impression formation and social inference also propose that perceivers vary their use of different attributes as a function of their motivation to judge a target accurately (e.g., Fiske, Lin, & Neuberg, 1999; Fiske & Neuberg, 1990). Specifically, according to these models, increased accuracy motivation (via internal motives, interdependence with the target, etc.) should decrease the use of social category information and increase the use of individuating personal information. The MCI model can be applied to directly test these hypotheses by providing a means for estimating the independent contributions of different cues, which, to date, has not been possible.

Context Effects on Person Perception

Another central goal of person perception research is to assess the independent contributions of target features (e.g., traits) and situational details in impression formation. Process models designed to account for the supposed under-use of social context on person perception (i.e., the "Fundamental Attribution Error") propose that inferences about the situation surrounding a person are made less efficiently than inferences about the person's traits (Gilbert, 1989; Trope, 1986). Accordingly, these models propose that cognitive load reduces the integration of situational information but does not impair the use of person information (e.g., personality traits) in person perception.

More broadly, a key question in person perception research concerns the joint contributions of person cues and context cues on impression formation. Among many other examples, researchers have investigated the contributions of background imagery (e.g., Brambilla et al., 2018), clothing cues (Freeman et al., 2011; Oh et al., 2020), and accessory items (e.g., tools or guns; Fessler et al., 2012), on person perception. In some cases, researchers have avoided making inferences about the contributions of each cue (e.g., Fessler et al., 2012); in others, cues are assumed to be integrated inversely from one another (e.g., Brambilla et al., 2018; Freeman et al., 2013; Xie et al., 2022). The MCI model provides a means for directly investigating such questions.

Intersectionality

All people simultaneously belong to multiple groups based on sex, race, age, etc. In recent years, increasing attention has been paid to how impressions are based not on a single social category, but rather the intersection of multiple categories (e.g., Kang & Bodenhausen, 2015). In focusing on the inherent intersectionality of people, this research has revealed considerable nuance in group-based judgments of and behavior toward other people. For example, judgments about a target's sex may vary as a function of target race (Johnson et al., 2012). Judgments of leadership ability may be affected by an interaction between the target's race and sexual orientation (Wilson et al., 2017). Basic intergroup bias favoring ingroups over outgroups may be attenuated if the target and perceiver share a common identity (e.g., Calanchini et al., 2022; Scroggins et al., 2016). However, the intersectional stereotyping literature has yet to disentangle the contributions of each category cue in an intersectional judgment. For example, the extents to which each social category plays a role in Black women being mistaken for and stereotyped as men more frequently than White women (e.g., Kang & Bodenhausen, 2015) is not clear. Do perceivers rely on Black cues more (stereotypically emphasizing masculine qualities), female cues less (stereotypically minimizing feminine qualities), or both? These kinds of questions are can be addressed with the MCI model.

Conclusion

The judgments we make about people are foundational to when, how, and why we treat them the way we do. Though, there is now an extensive body of literature on many facets of person perception, theoretical progress has been hindered by an inability to distinguish the independent contributions of multiple features in social judgment. Is the processing of social categories highly efficient? Does accuracy motivation reduce the use of social categories and increase the use of personalizing attributes, or both? Is the integration of situational constraints in understanding behavior particularly inefficient? More broadly, to what extent do people integrate personal and contextual features in person perception? What accounts for observations of social category intersectionality? Do certain features dominate impressions? These questions cannot be addressed effectively without disentangling the contributions of each source of information, something that is impossible with conventional measurement approaches. Applying the MCI model offers a solution to this long-standing problem.

References

Anderson, N. H. (1968). Likableness ratings of 555 personality-trait words. *Journal of personality and social psychology*, *9*(3), 272.

Asch, S. E. (1946). Forming impressions of personality. *The Journal of Abnormal and Social Psychology*, *41*(3), 258.

Batchelder, W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modeling. *Psychonomic Bulletin & Review*, *6*(1), 57–86. https://doi.org/10.3758/BF03210812

Becker, D. V., Kenrick, D. T., Neuberg, S. L., Blackwell, K. C., & Smith, D. M. (2007). The confounded nature of angry men and happy women. *Journal of personality and social psychology*, *92*(2), 179.

Bodenhausen, G. V. (1990). Stereotypes as judgmental heuristics: Evidence of circadian variations in discrimination. *Psychological Science*, *1*(5), 319-322.

Brambilla, M., Biella, M., & Freeman, J. B. (2018). The influence of visual context on the evaluation of facial trustworthiness. *Journal of Experimental Social Psychology*, *78*, 34-42.

Brewer, M. B. (1988). A dual process model of impression formation. In R. S. Wyer, Jr., & T. K. Srull (Eds.), A dual-process model of impression formation: Advances in social cognition (Vol. 1, pp. 1–36). Hillsdale, NJ: Erlbaum

Brewer, M. B. (2014). A dual process model of impression formation. In *Advances in Social Cognition, Volume I* (pp. 1-36). Psychology Press.

Brewer, M. B., & Feinstein, A. S. H. (1999). Dual processes in the cognitive representation of persons and social categories.

Burnham, K. P., & Anderson, D. R. (2004). Model selection and multimodel inference. *A practical information-theoretic approach, 2*.

Calanchini, J., Rivers, A. M., Klauer, K. C., & Sherman, J. W. (2018). Multinomial processing trees as theoretical bridges between cognitive and social psychology. In *Psychology of learning and motivation* (Vol. 69, pp. 39-65). Academic Press.

Calanchini, J., Schmidt, K., Sherman, J. W., & Klein, S. A. (2022). The contributions of positive outgroup and negative ingroup evaluation to implicit bias favoring outgroups. *Proceedings of the National Academy of Sciences*, *119*(40), e2116924119.

Darley, J. M., & Gross, P. H. (1983). A hypothesis-confirming bias in labeling effects. *Journal of Personality and Social Psychology*, *44*(1), 20.

Erdfelder, E., Auer, T. S., Hilbig, B. E., Aßfalg, A., Moshagen, M., & Nadarevic, L. (2009). Multinomial processing tree models: A review of the literature. *Zeitschrift für Psychologie/Journal of Psychology*, *217*(3), 108-124.

Fessler, D. M., Holbrook, C., & Snyder, J. K. (2012). Weapons make the man (larger): Formidability is represented as size and strength in humans. *PloS one*, *7*(4), e32751.

Fiske, S. T., Lin, M., & Neuberg, S. L. (2018). The continuum model: Ten years later. *Social cognition*, 41-75.

Fiske, S. T., & Neuberg, S. L. (1990). A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. In *Advances in experimental social psychology* (Vol. 23, pp. 1-74). Academic Press.

Freeman, J. B., & Ambady, N. (2009). Motions of the hand expose the partial and parallel activation of stereotypes. *Psychological science*, *20*(10), 1183-1188.

Freeman, J. B., & Ambady, N. (2011). A dynamic interactive theory of person construal. *Psychological review*, *118*(2), 247.

Freeman, J. B., Johnson, K. L., Adams Jr, R. B., & Ambady, N. (2012). The social-sensory interface: category interactions in person perception. *Frontiers in integrative neuroscience*, *6*, 81.

Freeman, J. B., Ma, Y., Han, S., & Ambady, N. (2013). Influences of culture and visual context on real-time social categorization. *Journal of experimental social psychology*, *49*(2), 206-210.

Freeman, J. B., Penner, A. M., Saperstein, A., Scheutz, M., & Ambady, N. (2011). Looking the part: Social status cues shape race perception. *PloS one*, *6*(9), e25107.

Gilbert, D. T. (1989). Thinking lightly about others: Automatic components of the social inference process. In J. S. Uleman & J. A. Bargh (Eds.), *Unintended thought* (pp. 189–211). The Guilford Press.

Hartmann, R., Johannsen, L., & Klauer, K. C. (2020). rtmpt: An R package for fitting response-time extended multinomial processing tree models. *Behavior Research Methods*, *52*, 1313-1338.

Heck, D. W., Arnold, N. R., & Arnold, D. (2018). TreeBUGS: An R package for hierarchical multinomial-processing-tree modeling. *Behavior research methods*, *50*, 264-284.

Hehman, E., Stolier, R. M., & Freeman, J. B. (2015). Advanced mouse-tracking analytic techniques for enhancing psychological science. *Group Processes & Intergroup Relations*, *18*(3), 384-401.

Hess, U., Adams Jr, R. B., & Kleck, R. E. (2004). Facial appearance, gender, and emotion expression. *Emotion*, *4*(4), 378.

Hess, U., Adams, R. B., Grammer, K., & Kleck, R. E. (2009). Face gender and emotion expression: Are angry women more like men?. *Journal of Vision*, *9*(12), 19-19.

Hess, U., Thibault, P., Adams Jr, R. B., & Kleck, R. E. (2010). The influence of gender, social roles, and facial appearance on perceived emotionality. *European Journal of Social Psychology*, *40*(7), 1310-1317.

Heycke, T., & Gawronski, B. (2020). Co-occurrence and relational information in evaluative learning: A multinomial modeling approach. *Journal of Experimental Psychology: General*, *149*(1), 104.

Hugenberg, K., & Bodenhausen, G. V. (2003). Facing prejudice: Implicit prejudice and the perception of facial threat. *Psychological Science*, *14*(6), 640-643.

Hütter, M., & Klauer, K. C. (2016). Applying processing trees in social psychology. *European Review of Social Psychology*, *27*(1), 116-159.

Johnson, K. L., Freeman, J. B., & Pauker, K. (2012). Race is gendered: how covarying phenotypes and stereotypes bias sex categorization. *Journal of personality and social psychology*, *102*(1), 116.

Kang, S. K., & Bodenhausen, G. V. (2015). Multiple identities in social perception and interaction: Challenges and opportunities. *Annual review of psychology*, *66*, 547-574.

Klauer, K. C., & Wegener, I. (1998). Unraveling social categorization in the" who said what?" paradigm. *Journal of Personality and Social Psychology*, *75*(5), 1155.

Krieglmeyer, R., & Sherman, J. W. (2012). Disentangling stereotype activation and stereotype application in the stereotype misperception task. *Journal of personality and social psychology*, *103*(2), 205.

Kunda, Z., & Thagard, P. (1996). Forming impressions from stereotypes, traits, and behaviors: A parallel-constraint-satisfaction theory. *Psychological review*, *103*(2), 284.

Leyens, J. P., Yzerbyt, V. Y., & Schadron, G. (1992). The social judgeability approach to stereotypes. *European review of social psychology*, *3*(1), 91-120.

Moshagen, M. (2010). multiTree: A computer program for the analysis of multinomial processing tree models. *Behavior Research Methods*, *42*(1), 42-54.

Norton, M. I., Vandello, J. A., & Darley, J. M. (2004). Casuistry and social category bias. *Journal of personality and social psychology*, *87*(6), 817.

Oh, D., Shafir, E., & Todorov, A. (2020). Economic status cues from clothes affect perceived competence from faces. *Nature human behaviour*, *4*(3), 287-293.

Payne, B. K., Hall, D. L., Cameron, C. D., & Bishara, A. J. (2010). A process model of affect misattribution. *Personality and social psychology bulletin*, *36*(10), 1397-1408.

Petsko, C. D., & Bodenhausen, G. V. (2020). Multifarious person perception: How social perceivers manage the complexity of intersectional targets. *Social and Personality Psychology Compass*, *14*(2), e12518.

Petsko, C. D., Rosette, A. S., & Bodenhausen, G. V. (2022). Through the looking glass: A lens-based account of intersectional stereotyping. *Journal of Personality and Social Psychology*.

Schmidt, O., Erdfelder, E., & Heck, D. W. (2022, March 14). How to Develop, Test, and Extend Multinomial Processing Tree Models: A Tutorial. https://doi.org/10.1037/met0000561

Scroggins, W. A., Mackie, D. M., Allen, T. J., & Sherman, J. W. (2016). Reducing prejudice with labels: Shared group memberships attenuate implicit bias and expand implicit group boundaries. *Personality and Social Psychology Bulletin*, *42*(2), 219-229.

Sherman, J. W., Klauer, K. C., & Allen, T. J. (2010). Mathematical modeling of implicit social cognition: The machine in the ghost. In B. Gawronski & B. K. Payne (Eds.), *Handbook of implicit social cognition: Measurement, theory, and applications* (pp. 156–174). The Guilford Press.

Sherman, J. W., Macrae, C. N., & Bodenhausen, G. V. (2000). Attention and stereotyping: Cognitive constraints on the construction of meaningful social impressions. *European review of social psychology*, *11*(1), 145-175.

Singmann, H., & Kellen, D. (2013). MPTinR: Analysis of multinomial processing tree models in R. *Behavior Research Methods*, *45*, 560-575.

Stahl, C., & Klauer, K. C. (2007). HMMTree: A computer program for latent-class hierarchical multinomial processing tree models. *Behavior Research Methods*, *39*, 267-273.

Stillerman, B. S., & Freeman, J. B. (2019). Mouse-Tracking to Understand Real-Time Dynamics of Social Cognition 1. In *A handbook of process tracing methods* (pp. 146-160). Routledge.

Stillman, P. E., Shen, X., & Ferguson, M. J. (2018). How mouse-tracking can advance social cognitive theory. *Trends in cognitive sciences*, *22*(6), 531-543.

Swencionis, J. K., & Fiske, S. T. (2013). More human: Individuation in the 21st century. In *Humanness and dehumanization* (pp. 284-301). Psychology Press.

Trope, Y. (1986). Identification and inferential processes in dispositional attribution. *Psychological review*, *93*(3), 239.

Wilson, J. P., Remedios, J. D., & Rule, N. O. (2017). Interactive effects of obvious and ambiguous social categories on perceptions of leadership: When double-minority status may be beneficial. *Personality and Social Psychology Bulletin*, *43*(6), 888-900.

Xie, S. Y., Thai, S., & Hehman, E. (2023). Everyday perceiver-context influences on impression formation: No evidence of consistent effects. *Personality and Social Psychology Bulletin*, *49*(6), 955-968.

Yzerbyt, V. Y., Dardenne, B., & Leyens, J.-Ph. (1998). Social judgeability concerns in impression formation. In V. Y. Yzerbyt, G. Lories, & B. Dardenne (Eds.), *Metacognition: Cognitive and social dimensions* (pp. 126-156). London: Sage.

Yzerbyt, V. Y., Schadron, G., Leyens, J. P., & Rocher, S. (1994). Social judgeability: The impact of meta-informational cues on the use of stereotypes. *Journal of Personality and Social psychology*, *66*(1), 48.