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THEORETICAL NOTE

Measuring the Impact of Multiple Social Cues to Advance Theory in Person Perception Research

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Forming impressions of others is a fundamental aspect of social life. 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, and so forth. 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, after describing these limitations and their constraints on theory testing and development, we present a multinomial processing tree model as a computational solution to the problem. Specifically, the model distinguishes the contributions of multiple cues to social judgment. We describe an empirical demonstration of how applying 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

Supplemental materials: https://doi.org/10.1037/rev0000503.supp

Since the publication of Asch's (1946) seminal work, perhaps the most fundamental objective in the research on person perception has been to understand how people combine the implications of multiple and varied features in judging others (see also Anderson, 1968). Cues relating to social group membership (e.g., race), personality traits (e.g., extraversion), and 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 of another person. Though many influential models have been proposed to account for this complex task, testing them has been hindered by a limitation in measurement. In turn, this limitation has significantly slowed theoretical progress. In this article, we detail the nature of the problem before offering a solution in the form of a computational modeling approach.

Theoretical Background

Models of person perception often posit how multiple features are integrated into a judgment. One of the prevailing claims that these models make is that integrating different features occurs through a competitive process, such that relying more on one feature implies relying less on others. We refer to this as the *inverse relativity* assumption. 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, 2018) 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 et al.'s (2022) lens model, which proposes that people use a variety of contextually activated lenses in perceiving others. However, according to the model, once one social category lens (e.g., race) has been activated, the use of other categories is necessarily diminished.

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Some of the ideas and data presented in this article have been presented at research conferences hosted by the European Association of Social Psychology (Krakow, 2023) and the Midwestern Psychological Association (Chicago, 2022). These ideas and data will also be presented at the upcoming research convention hosted by the Association for Psychological Science (San Francisco, 2024). For a brief period, some of these ideas and data were also shared on the personal website of Samuel A. W. Klein (https://www.sawklein.com). The data presented in this article were collected in an experiment that was approved by the University of California Institutional Review Board (Protocol Number: 223029; Experiment Name: *SHER806*). Data, code, and instructions for implementing the multicue integration model are available at the Open Science Framework and is accessible at https://osf.io/gxbc5/. This research was supported by the Directorate for Social, Behavioral and Economic Sciences National Science Foundation Grant BCS 2215236 awarded to Jeffrey W. Sherman.

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Beyond the inverse relativity assumption, another prevailing view in the person perception literature is that certain features *dominate* person perception (cf. Petsko & Bodenhausen, 2020)—that is, some cues are integrated into judgments by default and are highly impactful in determining social judgments. These models generally suppose that social category cues, particularly unambiguous visible cues to gender, race, and age, are processed more efficiently with fewer attentional resources than other cues (e.g., Brewer, 1988; Fiske & Neuberg, 1990). When person information is perceptually disfluent (e.g., inverted face; Cloutier et al., 2005) or a perceiver's cognitive or motivational resources are low (e.g., via a cognitive load task; Wigboldus et al., 2004), social categorization and, by extension, stereotyping are thought to remain active. However, the processing of cues that refer to the personal individuating attributes of people, such as traits, states, and behaviors, is thought to operate insufficiently under such impoverished circumstances (e.g., Sherman et al., 2000; Swencionis & Fiske, 2013), augmenting the relative impact of social categories.

Of course, inverse relativity and category dominance are not the only perspectives in person perception research. For example, the social judgeability model (Leyens et al., 1992; Yzerbyt et al., 1994, 1998) predicts that stereotyping is more likely when individuating features are available, if 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). Thus, this perspective posits that greater individuation may increase categorization (i.e., a direct relationship), contrasting the inverse-relativity perspective.

A class of network models (e.g., Freeman & Ambady, 2011; Kunda & Thagard, 1996) eschews both the inverse-relativity and category dominance perspectives, assuming that all available features may be integrated, as in early models of impression formation (e.g., Anderson, 1968; Asch, 1946). They allow for the use of different features to be positively correlated, negatively correlated, or not correlated at all (Freeman et al., 2012). They also suggest that aspects of the perceiver can affect which features are more or less dominant during the construal process (Freeman et al., 2020; see also Bless & Schwarz, 2010). Altogether, there is great flexibility in the model to account for almost any pattern of feature integration. This is both a strength and weakness of the model, as it does 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.

A Multicue Measurement Problem

Clear tests of the models laid out above require the ability to measure the separate impacts of multiple features on impressions and their theoretically proposed relationships (e.g., race-dominating impressions over behavior). For instance, adequately testing whether cognitive load decreases individuation and increases categorization (e.g., Fiske & Neuberg, 1990), or decreases both processes (e.g., Spears et al., 1999), requires that the impacts of social categories and person-specific cues be distinguished from each other. Unfortunately, conventional measurement approaches are unable to do so.

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 smiling 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.

Consider also 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 to support prominent dual-process models and their assumptions about inverse-relativity and social category dominance: People make more stereotypic judgments when they have diminished processing capacity and motivation. Although findings like this serve as important illustrations, the extent to which different information contributes to these effects is unclear. Does reducing cognitive resources increase the use of social categories, decrease the use of individuating details about the person, or both? Alternatively, both features may be relied upon more or less, with the change in one being greater than the other. In all cases, the outcome is an increase in stereotypic judgments.

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 (Hugenberg & Bodenhausen, 2003). Though an important demonstration of the effects of stereotypes on emotion perception (see also Weisbuch & Ambady, 2008), the extent to which different types of information contribute to the effect is unclear. Does construing Black faces quickly becoming angry reflect relying on race more, relying on facial expressions less, or some combination of changes in both features?

As a final illustration, consider mouse-tracking tasks, which 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. 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).

However, although mouse-tracking measures are excellent indicators of parallel activation and response conflict, they cannot distinguish the extents to which the two different sources of information influence 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 at the expense of race before a transition to a greater impact of race at the expense of clothing. However, the varying influence of each feature cannot be distinguished from the other. The measures are inherently relative and pit the use of each cue against the other in an inverse fashion.

A Multicue Integration Model

Here, we propose a solution to the multicue measurement problem in the form of a computational model that we named the multicue integration (MCI) model. The MCI model is a multinomial processing tree (MPT), a class of cognitive models comprised of a set of equations to identify and measure the extent of processes underlying responses in a task (for reviews, see Batchelder & Riefer, 1999; Calanchini et al., 2018; Erdfelder et al., 2009; Hütter & Klauer, 2016; Sherman et al., 2010). Like any MPT, the MCI model is built on a small set of parameters—C_1, C_2, and g—with each parameter reflecting the probability of a unique cognitive-processing state (e.g., the integration of a target's facial expression into an impression). The C_1 and C_2 parameters each reflect the probability of a unique source of information being used to form judgments, whereas g reflects a response bias toward one response over another. If targets in an emotion classification task vary in both facial expression and sex, then C_1 might be assigned to reflect the probability of facial expressions being used to classify target faces, whereas C_2 might be assigned to reflect the use of sex-differentiating features for those very same classifications.

Visually, the relationships among these parameters can be depicted as a processing tree, as seen in Figure 1. The MCI model assumes that the probability of using the information assigned to C_2 (e.g., facial expressions) is contingent upon the probability that using the information assigned to C_1 (e.g., sex-differentiating features) is insufficient for deriving a particular judgment [$(1 - C_1) \times C_2$]. Although the parameters and their relationships among one another remain the same across judgment tasks, the number of equations used to model the data are determined by the number of unique responses on that task. That is, the MCI model produces an equation for each unique response that can be observed in a judgment task. A task with 12 unique responses would require 12 unique equations, derived from the MCI model's parameters.

It is noteworthy to further highlight what the C_1 and C_2 processing parameters reflect. Traditional computational cognitive models focus on the various mechanisms (e.g., activated associations, recognition memory, correct response detection) that turn input information into social judgments. MPTs have been very useful for such investigations (e.g., Heycke & Gawronski, 2020; Klauer & Wegener, 1998; Krieglmeyer & Sherman, 2012), as they traditionally quantify how often the various mechanisms work to generate those judgments. The MCI model, however, is unique in that it focuses on quantifying the extent to which specific input features are used to form social judgments. The C_1 and C_2 parameter estimates encapsulate the cumulative processing of these features, across whatever mechanisms may be involved. That is, the MCI model offers a quantitative assessment on each feature's impact, summed across all the mechanisms by which they may be used to derive judgments. To illustrate more fully, we describe an experiment designed to test the model's validity for a particular judgment task and its capacity for theory testing and development in person perception research.

Demonstrating the MCI Model

Participants ($N = 593$; Klein & Sherman, 2024) classified faces varying in sex (male, female) and facial expression (scowling, smiling).[1] Using morphing techniques described in the Supplemental Materials, both cues were manipulated to appear either ambiguous or unambiguous. By assigning participants to classify faces by gender or emotion, the relevance of sex and expression were manipulated between participants.

It is important to note that the MCI model measures the use of available information (cf. Higgins, 1996) that is cued by features of the target. In this empirical demonstration, the MCI model assumes that sex features cue available information related to gender (e.g., gender stereotypes) and that facial expressions cue available information related to emotion. Hereinafter, we refer to the target-level features as the cues to available information that the MCI model assumes is being processed by perceivers to derive social judgments. Sex features are referred to as gender cues, and expressions are referred to as emotion cues.

As previously stated, the number of equations that the MCI model derives depends on the number of unique responses in the task. Here, the MCI model derives eight unique equations (2 [Judgment: man, woman; or angry, happy] × 2 [Gender Cues: male, female] × 2 [Emotion Cues: scowling, smiling] equations). For example, separate equations were derived for predicting how often smiling male faces were classified as a man versus woman.

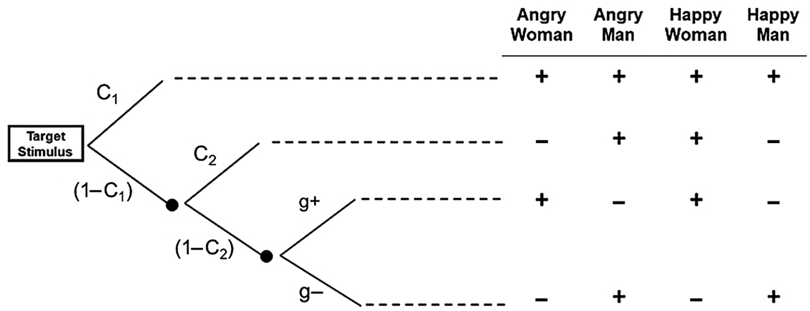
Following along the tree in Figure 1, for the gender classification task, the probability of classifying a happy male face as a man is predicted by the joint contributions of male facial cues [C_1] and a tendency to categorize faces as men whenever gender and emotion cues are insufficient to derive a coherent judgment [$(1 - C_1) \times (1 - C_2) \times (1 - g)$]—that is, a response bias toward *man*. The compliment of that probability, the equation for classifying a happy male target as a woman, is predicted by the joint contributions of a smiling face [$(1 - C_1) \times C_2$] and a tendency to categorize faces as women whenever gender and emotion cues are insufficient to derive a coherent judgment [$(1 - C_1) \times (1 - C_2) \times g$]—that is, a response bias toward *woman*. Therefore, by simply following the paths along the tree, the equations predicting each unique response can be derived (the full set of equations are displayed in the Supplemental Materials).

A more detailed discussion of the mechanics underlying MPTs and their implementation is beyond the scope of this text. For a more detailed introduction to MPTs, we recommend a recent article by Hütter and Klauer (2016). For more details on the implementation of MPTs, we recommend general (Schmidt et al., 2023) and software-specific (Hartmann et al., 2020; Heck et al., 2018; Moshagen, 2010; Singmann & Kellen, 2013; Stahl & Klauer, 2007) tutorials. To closely follow the approach taken for the MCI model in this article, we recommend both Heck et al.'s (2018) introduction to the *TreeBUGS* package in R and our additional online materials (https://osf.io/gxbc5/). Regarding our additional online materials, we have included data files and well-commented coding scripts (in R), as well as the MCI model file, so that readers may implement the necessary preprocessing steps, estimate the MCI model, and analyze the parameter estimates. We have also included a thoroughly commented text file that interprets each of the MCI model equations.

[1] Male and female models were randomly selected from the Chicago Face Database (Ma et al., 2015). Norming data from the Chicago Face Database indicate >95% agreement of each model's gender, when displaying a neutral expression. These models were directed to display clear scowling and smiling expressions. The images capturing these expressions were selected for our experiment.

Figure 1

The MCI Model and Its Predicted Responses to Gender Classifications



Note. Diagram of the MCI model used to measure person perception data from a paradigm in which judgments were made of targets varying in gender 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. C_1 = use of gender cues; C_2 = use of emotion cues; g = response bias; [+] = correct response; [−] = incorrect response; MCI = multicue integration.

MPTs are theoretically derived models, and the MCI model relies on well-established stereotypes that we assume participants rely on when forming judgments. Here, the MCI model relies on the stereotype linking men (women) and negative (positive) emotions: The model assumes that emotion cues are used when smiling faces are classified as woman and scowling faces as man but not the other way around. For example, the equation for judging a smiling male face as woman $[(1 - C_1) \times C_2 + (1 - C_1) \times (1 - C_2) \times g]$ includes the assumption that smiles are associated with woman and not man (see Becker et al., 2007 and Hess et al., 2009). These assumptions are required to identify the model and can be tested by examining whether the model adequately predicts the observed responses (i.e., model fit).

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.

Applying the MCI Model

First and foremost, the MCI model fits well to both the gender classification judgments, median individual $T_{1\ p\ \text{value}} = .558$, Aggregate $T_{1\ p\ \text{value}} < .001$, aggregate $T_{2\ p\ \text{value}} = .002$, $w = .02$, and emotion classification judgments, median individual $T_{1\ p\ \text{value}} = .538$, aggregate $T_{1\ p\ \text{value}} = .094$, aggregate $T_{2\ p\ \text{value}} = .192$, $w < .01$, albeit far better fitting for emotion classification judgments. Assessment of model fit includes visual examination of the posterior predictions against the observed response frequencies and covariances. Visually, the model appears to fit quite well to both gender and emotion classification judgments (see Supplemental Figures S1–S4).[2]

Parameter Comparisons. If the MCI model measures the distinct contributions of gender and emotion information, we would expect the estimated use of each cue to be greater when it was relevant versus irrelevant to the intended judgment. Indeed, gender cues were used more and emotion cues were used less during gender versus emotion classification. We would also expect that task-relevant cues (e.g., gender cues during gender classification) would be used less when ambiguous. Aligned with this expectation, introducing ambiguity in gender cues decreased their use during gender classification (Figure 2), whereas introducing ambiguity in emotion cues decreased their use during emotion classification (Figure 3).

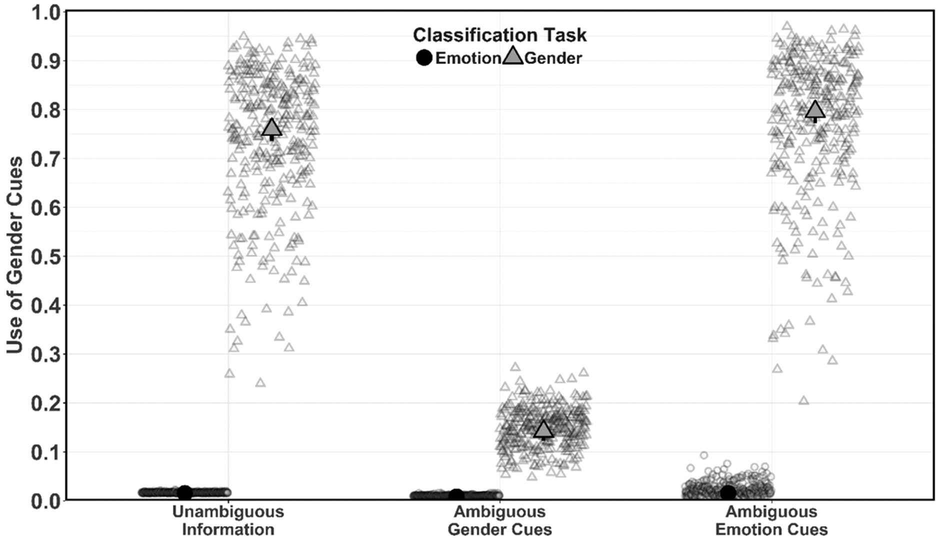
Parameter Correlations. As we previously discussed, a prominent assumption in the person perception literature is that two features are integrated in a competition (e.g., Fiske & Neuberg, 1990). If one feature contributes more, it is at the expense of the other feature's contribution to the judgment. However, alternative relationships have also been proposed, such as positive associations between the two features (e.g., Leyens et al., 1992)—categorization is sometimes thought to increase when individuation does as well. To diagnose these competing accounts, we can examine the correlation between the use of each source of information. Here, we focus on trials when neither feature was ambiguous. Note that credible correlations are considered those excluding zero in their 95% Bayesian credibility intervals (95% BCIs). For gender classification judgments, the MCI model identified a credible and positive correlation between the use of gender and emotion cues, $r = .64$, 95% BCI [.29, .92]. For emotion classification judgments of the same targets, however, the model failed to identify any association between the use of the two cues, $r = .13$, 95% BCI [−.92, .90].[3]

Model Comparison. As we have noted, extant theory contends with competing predictions about which cues are processed by default. Arguably the most prominent assumption is one in which social categorization serves as the default process. Regardless of alternative sources of information or the intended judgment, social categories are often thought to be integrated into impressions (Brewer, 1988; Fiske & Neuberg, 1990; Hugenberg et al., 2010). Alternative perspectives suggest that the intended judgment—that is, a perceiver's goal—and other motives determine which information is more likely to be integrated into an impression by default (Freeman et al., 2020; Petsko et al., 2022; Bless & Schwarz, 2010).

[2] More technical details regarding the estimation of the MCI model are beyond the scope of this article's main text. Those details, including the estimation procedure we applied and descriptions of the various measures of model fit, are thoroughly discussed in the Supplemental Materials.

[3] Correlations for all three ambiguity conditions were averaged using Fisher z transformations.

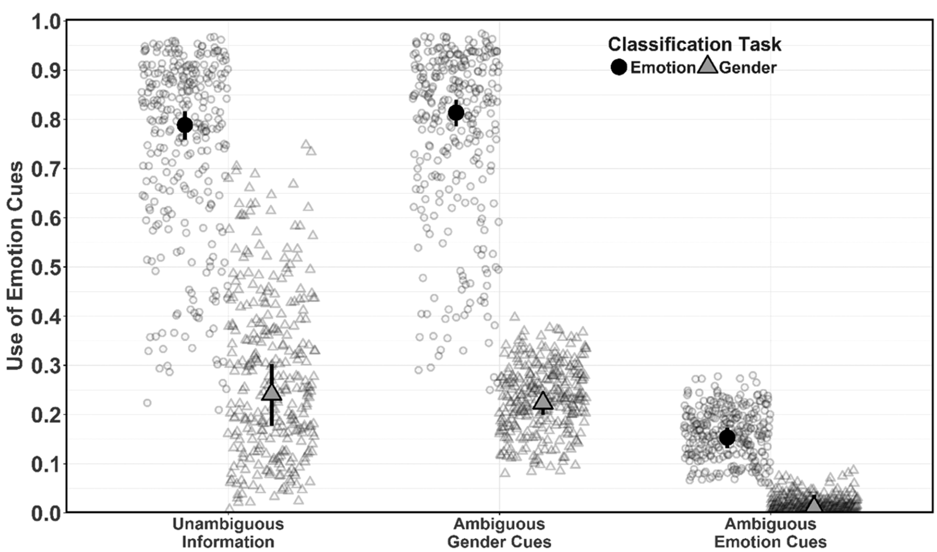
Figure 2
Estimated Use of Gender Cues During Face Classification



Note. Markers reflect the estimated use of gender cues during face classification by gender (triangles) or emotion (circles). Solid markers reflect aggregate-level estimates, whereas empty markers reflect individual-level estimates. The *x*-axis reflects whether target face stimuli were presenting ambiguous sources of information. The *y*-axis reflects the estimated probability of relying on gender cues when classifying target faces. Error bars signify 95% Bayesian credibility intervals around the aggregate-level estimate.

A strength of the MCI model is that it offers a framework within which to formalize and test competing default-processing assumptions. The model's equations establish conditional relationships among the parameters, assuming that the use of the second feature is contingent upon the first feature being insufficient for producing the judgment $[(1 - C_1) \times C_2]$. By fitting the MCI model both when C_1 is assigned to one cue versus the other, we can identify whichever model variant better characterizes the data (for similar approaches,

Figure 3
Estimated Use of Emotion Cues During Face Classification



Note. Markers reflect the estimated use of emotion cues during face classification by gender (triangles) or emotion (circles). Solid markers reflect aggregate-level estimates, whereas empty markers reflect individual-level estimates. The *x*-axis reflects whether target face stimuli were presenting ambiguous sources of information. The *y*-axis reflects the estimated probability of relying on emotion cues when classifying target faces. Error bars signify 95% Bayesian credibility intervals around the aggregate-level estimate.

see Calanchini et al., 2022; Laukenmann et al., 2023). Here, we demonstrate this procedure by fitting the MCI when C_1 reflects gender processing and again when it reflects emotion processing.

We differentiate and compare the two versions with a response time extension to the MCI model (see Klauer & Kellen, 2018). After fitting both versions of the model to classifications of unambiguous faces, we compared their deviance information criteria (DIC) to determine which version offers a better characterization of the observed judgments. We relied on $\Delta\text{DIC} > 2$ as a cutoff for adequate evidence in favor of one model over another (Burnham & Anderson, 2002). Comparison of the two models yielded substantive evidence for a gender default model, $\Delta\text{DIC} = 295.53$. That is, for social category and emotion judgments, gender cues were integrated by default, whereas emotion cues were better characterized as being used if gender cues alone were insufficient to derive the judgment. It remains an open question as to whether all social categories dominate person perception. This procedure, therefore, should be replicated and generalized across various social categories (e.g., race, age) and identity-specific cues (e.g., other emotion cues, behaviors) and across various intended judgments (e.g., gender classification, gender-typical vs. gender-atypical trait impressions).

Summary

This initial pilot study demonstrates that the MCI provides an accurate account of multifeature integration in person perception. Further, the results highlight the model's potential for theory testing and development. For instance, the lack of negative correlation between the use of two clear cues challenges the inverse relativity assumption that increases in the use of one feature should coincide with decreases in the other. Obviously, this singular empirical demonstration does not offer a thorough test of inverse relativity, but it does highlight the need for research that applies this technique to thoroughly examine *how* various cues are integrated together into social judgments.

We also demonstrated how the MCI model can be applied to test dominance assumptions in person perception research, which generally assume that one feature (usually representing social categories) is used more efficiently, acts as a default, and is more impactful in judgments than other features. Here, we find that gender cues were, indeed, better characterized as a default process, even when emotion cues were more relevant to the judgment at hand (i.e., emotion classification). Again, these data are illustrative but preliminary. Considerable further work will be required to draw any broad claims about the kinds of features that tend to dominate and the conditions under which they do so.

Further Applications of the MCI Model

The MCI model offers a flexible solution for testing key questions and theories surrounding person perception that can be applied to most tasks in which judges must select among discrete options. In this article, we introduce and initially validate the MCI model as one that can capture information processing behind binary classifications of faces by gender and emotion. However, the same framework could be applied to judgments of race, age, or personality traits or to decision making given a variety of kinds of available information (e.g., hiring context; Axt et al., 2018), so long as each target belongs to only one level of each dimension measured by the MCI model. MPTs, like the MCI model, can also be redrawn to accommodate a broader range of data, including data from tasks with three response options (e.g., Klauer & Wegener, 1998). The model can also be extended to include *both* discrete responses and continuous data, such as response times (Heck & Erdfelder, 2016; Klauer & Kellen, 2018) and mouse tracking (Heck et al., 2018), if both are presumed to be integral for explaining the cognitive processing underlying judgments.

Consider the benefits of integrating response times into the MCI model. Doing so could (a) estimate the speeds at which different features lead to judgments and (b) test the temporal order by which two features are processed during person perception. As previously discussed, social categorization is thought to occur prior to the processing of other, more identity-specific information (e.g., Fiske & Neuberg, 1990; Hugenberg et al., 2010). Including response times into the MCI model framework, and subsequently testing the temporal order between social categories and more identity-specific cues, offers a direct test of this assumption. Although we have not yet developed versions of the MCI model to accommodate nonbinary discrete responses or the inclusion of continuous data, it is certainly possible to do so.

Testing Dominance Assumptions of Person Perception Models

As mentioned earlier, another facet of the general assumption that social categories dominate person perception is the claim that they are 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 features, 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 emotion expressions, 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 et al., 1999, 2018; 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 should 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.

The MCI model can also be applied to test the extent to which various features are used depending on what other information is also available. Our empirical demonstration measured the use of gender and emotion cues to classify faces. However, if those faces varied in gender and race cues instead, would gender cues be used differently than when emotion was the alternatively available information? By implementing the MCI model across various information pairings (e.g., gender and emotion cues, gender and race cues, gender and trait cues), we can better understand the extent to which the use of specific features is context general versus context-specific in person perception.

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 underuse 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., 2021). The MCI model provides a means for directly investigating such questions.

Multiply Categorizable Person Perception

All people simultaneously belong to multiple groups based on gender, race, age, and so forth. In recent years, increasing attention has been paid to how impressions are based not on a single social category, but rather multiple categories (e.g., Kang & Bodenhausen, 2015). This research has revealed considerable nuance in group-based judgments of and behavior toward other people. For example, judgments about a target's gender 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 literature on judgments of multiply categorizable targets has yet to disentangle the contributions of each category cue. 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. Theoretical progress in person perception research has been hindered by an inability to distinguish the contributions of multiple available cues to social judgment. Is the processing of social categories highly efficient? Does accuracy motivation reduce the use of social categories and increase the use of identity-specific cues 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? Do certain features dominate impressions? If so, are these dominant features processed first, by default, more efficiently, more often, or by some combination of these facets? These questions cannot be addressed effectively without disentangling the contributions of each source of information. The MCI model offers a solution to this multicue measurement problem.

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