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Language Bias in Child Welfare

Approaches to Identifying and Studying Biased Language to Advance Equitable Child Welfare Practice

Introduction

Marginalized families are overrepresented in the U.S. child welfare system and persistently demonstrate worse well-being, permanency, and safety outcomes. Parents who have disabilities; are of lower socioeconomic status; and are Black, Indigenous, or persons of color (BIPOC) are significantly more likely to be reported to child protective services, have substantiated maltreatment allegations, and experience the removal of a child from their home (Beniwal, 2017; Chambers & Ratliff, 2019). The disproportionate involvement of BIPOC children in child welfare puts them at a disadvantage early in their childhoods. Their entry into an institution rooted in racism makes them more vulnerable to maltreatment in out-of-home care, longer stays in care, and a lower likelihood of reunification with their families than white children (Bruster et al., 2019; Edwards et al., 2021).

Implicit biases of child welfare professionals may drive inequitable responses to families and disparate outcomes. Implicit bias refers to

At a Glance

Audience. Child welfare researchers, evaluators, and policymakers.

Purpose. To provide an overview of biased language in child welfare case practice and strategies to identify and study it.

Takeaways

- The implicit biases of child welfare professionals are manifested in their spoken and written language.
- Concepts for understanding biased language include labeling, abstract versus concrete language, and sociolinguistic inequality.
- Methods to uncover and study biased language include text mining, machine learning, and dictionary-based analysis.
- Improved understanding of biased language contributes to more effective practices to address child welfare system disparities.

unconscious attitudes or stereotypes that affect the interpretation of information and subsequent decisions and responses (Bruster et al., 2019). Human service professionals make critical decisions as they gather, interpret, and share information about families; however, few studies examine bias in child welfare practice (Beniwal, 2017) that occurs in the context of stressful work conditions such as high caseloads, which may increase the influence of implicit bias on decision making (Johnson et al., 2016). Yu (2016) suggested that neurological processes in stressful situations can lead to decisions based on emotion and habit rather than objective analysis.

Bias may be reflected in the spoken and written language used by child welfare professionals. Language is one of the most powerful indicators and transmitters of bias in child welfare and other human service settings. Biased language refers to elements of oral or written speech that indicate or suggest bias towards certain individuals, which may perpetuate prejudicial beliefs or demeaning attitudes based on age, disability, gender, racial and ethnic identity, sexual orientation, and socioeconomic status (American Psychological Association, 2021). Biased language is characterized by systematic asymmetry in word choice (i.e., a pattern of using certain words, expressions, or descriptions) that reflects stereotypical expectations of a group or individual (Beukeboom & Burgers, 2017), stigmatizing terms used to describe individuals (Werder et al., 2022), and language patterns that indicate that an individual's contributions to discourse are not encouraged or valued (Coulmas, 2003). Recurring language patterns that reflect bias are often not conscious and may be difficult to censor (Franco & Maass, 1996). For this reason, linguistic studies have been conducted in fields such as healthcare to detect implicit bias among professionals and whether it affects clinical decision-making and is associated with poorer medical outcomes among BIPOC patients (Goddu et al., 2018). Similar studies in the child welfare field may be helpful in understanding whether language bias reflects or influences practice bias and contributes to disparate outcomes.

This brief provides an overview of key concepts for understanding biased language, their applicability to child welfare practice, and methods for identifying and studying bias expressed through oral and written speech.

"…The system recognizes that these disproportionate numbers exist. But what child protection agencies fail to appreciate is the impact that implicit bias has upon these outcomes. The failure to fully recognize this precursor to disproportionality has the unintended effect of endorsing it."

—Beniwal, 2017, p. 1021

Concepts and Models for Understanding Biased Language

Research in linguistics has posited concepts and models that are useful for uncovering, categorizing, and measuring bias. These constructs illuminate and explain subtle changes in language that may indicate stereotyping (Beukeboom & Burgers, 2017) or reveal power differentials and inequality in language exchanges (Danescu-Niculescu-Mizil et al., 2013; Philips, 2004).

Labeling

Labels represent categories of people, such as professions (e.g., restaurant servers, doctors), gender (e.g., male, female, nonbinary), and race and ethnicity (e.g., Black, Asian, White, Latino). Linguists have examined how labels are used to identify and assign characteristics to individuals or groups; they can reduce group members' individuality and lead to judgments based on stereotypical associations rather than on concrete and objective information (Beukeboom & Burgers, 2019). The use of nouns or noun labels evokes stronger stereotypical expectations in a hearer than adjectives (e.g., referring to someone as a "foster youth" rather than a "youth in out-of-home placement"). This tendency has been observed in studies across multiple languages (Carnaghi et al., 2008).

Noun Labels

- **Adjectives** may be used to describe characteristics of individuals (e.g., "*He is **Latino***").
- A **noun label** (e.g., "*He is **a Latino***") evokes stronger stereotypical expectations associated with a labeled group.
- **Plural noun labels** (e.g., "***Latinos** speak Spanish*") presume characteristics are shared by all individuals in a labeled group.

(Carnaghi et al., 2008)

Linguistic Category Model

The linguistic category model (LCM) classifies language on a continuum from abstract to concrete (Semin & Fiedler, 1991). Language elements such as direct-action verbs (e.g., "show," "tell") are concrete and express a neutral perspective; more abstract language such as adjectives (e.g., "hostile," "exemplary") express a speaker's interpretation of events (Wigboldus et al., 2000). When a speaker describes someone's actions that are "expected" (i.e., because they reflect what are perceived as enduring traits of an individual), more abstract language is often used. On the other hand, concrete descriptions of a person's actions imply that the observed behavior is unusual and situational (Wigboldus et al., 2000). The use of abstract language by child welfare and other human service professionals may reflect generalizations about a child or parent that are aligned with their expectations of an entire group of people. The LCM continuum and associated examples are shown in exhibit 1.

Exhibit 1. Linguistic Category Model: Concrete-to-Abstract Continuum

Most concrete: descriptive action verb	Concrete: interpretive action verb	Abstract: state verb	Most abstract: adjective
• Refers to a *specific event* • Information is *objective* and easily verified • Information has a *neutral* connotation • Less apt to reflect and transmit *bias*	• Refers to a *specific event* • *Interprets* rather than simply describes behavior • Has *positive or negative* connotations • May reflect and transmit *bias*	• Expresses the *emotional consequence* of an action and/or is a state that exists *over time* • May reflect and transmit *bias*	• Does *not refer* to a specific event • Associated with *positive or negative* connotations • Implies an *enduring, stable trait* • Most apt to reflect and transmit *bias*
Sample sentences			
• She **explained** her relationship with her daughter during the team meeting. • Mr. Jones **showed** his son how to put away toys at the visit. • The client **told** the clinic staff he did not want to undergo the drug test.	• She **exaggerated** the closeness of her relationship with her daughter. • Mr. Jones **helped** his son at the visit. • The client **avoided** the drug test at the clinic.	• She is **angry** about her daughter. • Mr. Jones **loves** his son. • The client **dislikes** treatment.	• She is **hostile**. • Mr. Jones is **exemplary**. • The client is **noncompliant**.

Source: Semin & Fiedler, 1991.

The LCM is useful for exploring how group dynamics influence language across the continuum from concrete to abstract. For example, when members *within* a group describe individuals *outside* that group, they may use more abstract language that reflects stereotypical expectations of those outside-group individuals (Kurz & Lyons, 2009). This tendency is augmented when members of a group who are similar in socioeconomic or educational status discuss an outside individual of a different status (Moscatelli et al., 2008). For example, in settings such as child welfare courtroom hearings, “higher status” human service and judicial professionals may discuss families in a manner that conveys and generates biased information and judgments.

Once an individual is labeled, information aligning with stereotypes associated with the label is more likely to be communicated by the speaker; furthermore, that stereotypical information is more likely to be recalled by the hearer (Kashima, 2000). In human service fields, such as healthcare and child welfare, stereotypical expectations can spread when one professional documents information using biased language, which in turn evokes biased expectations among other providers who refer to these materials (Himmelstein et al., 2022). In a child welfare context, repeated copying of and references to language in documents such as maltreatment intake reports (e.g., “offender,” “drug abuser”) may be an important conduit of bias. Promoting the use of neutral language early in a case could reduce the transmission and perpetuation of biased information among professionals.

Study Example: Identifying Labels to Reduce Bias in Child Welfare Practice

An evaluation by Agosti (2011) of child welfare practice changes in California studied efforts to reduce bias toward families, including the use of neutral language in child maltreatment reports. This involved partnering with families likely to experience bias to develop a list of “hot words” or “buzzwords” (e.g., “unfit parent”) that could signal bias. When reporters of suspected child maltreatment used buzzwords, intake workers questioned the callers to obtain more concrete descriptions of the behaviors and characteristics of the alleged victims and/or perpetrators. Exhibit 2 provides a hypothetical example of a caller statement and how it could be rephrased and documented in a more objective manner.

Exhibit 2. Intake Practice to Elicit and Document Objective Family Information

Caller: subjective statement	Intake worker: intervening questions	Caller: objective description	Intake worker: documents information
The counselor said Bobby always comes to school filthy.	Could you describe exactly how he was dressed and how he looked? How often did that happen?	The counselor said Bobby came to school wearing the same clothing several days in a row and wore an oversized, torn, and dirty jacket.	The school counselor reported Bobby wore the same clothing with an oversized, torn, dirty jacket several days in a row.

This practice change of eliciting and documenting more objective information, in combination with other agency reform efforts, reduced the likelihood of maltreatment substantiations among Black and Native American children and has contributed to broader recommendations regarding the use of neutral language to document information on families (Capacity Building Center for States, 2021).

Sociolinguistic Inequality

Sociolinguistics examines how language is associated with social roles and status and how patterns of speech are related to an individual's social characteristics (e.g., economic class, gender, age, race, ethnicity; Coulmas, 2003). Social inequality can be expressed and amplified through language when it conveys or implies the relative value of an individual's contribution to a conversation or other social interaction—the speech of individuals with greater "value" is encouraged, whereas participation by individuals who are less valued may be dismissed, constricted, or disallowed (Philips, 2004).

Speakers with higher social status or authority have a higher level of influence over social interactions (Voigt et al., 2017). They may be less motivated to use politeness strategies, such as referring to an individual by name, and they may deliberately reduce politeness to heighten their own power and authority (Danesco-Niculescu-Mizel et al., 2013). In child welfare contexts, the status differential between child welfare professionals and families may result in bias that constricts the speech of those with less power. This bias may be exacerbated in highly regimented bureaucratic settings in which strategies used to control language are unequally applied and where participation is restricted for certain individuals. Exhibit 3 presents examples of language that may be used by an individual with high social power and status (a judge interacting with parents, caseworkers, and attorneys in a courtroom setting) to encourage or discourage another person's speech.

Exhibit 3. Indicators of Control Over Speech

Indicator of status or control of speech	Example	Connotation
Referring to an individual by name or by role	*Is Ms. Daniels present?* versus *Is the mother present?*	Addressing by name establishes an individual as unique and distinctive. Addressing by role implies the individual is personifying characteristics of the role.
Presence or absence of greeting an individual	*Ms. Daniels, it is nice to see you in court* versus Judge greets the attorneys at a hearing but does not greet the parents.	Greeting an individual acknowledges their value and that their presence should be recognized. Absence of greeting suggests less power or status.
Permitting or denying an individual the opportunity to speak	*Ms. Daniels, please tell us about what happened on Saturday* versus *Ms. Daniels, your attorney will speak for you.*	Giving an individual the opportunity to speak acknowledges they can affect the interaction or influence a situation. Denying permission implies they have no relevant information or power.

Indicator of status or control of speech	Example	Connotation
Ratification: acknowledging an individual's speech and its content	*So, what you are saying, Ms. Daniels, is that you were not aware of this requirement?*	Information provided by the individual is heard and accepted as valid.
Acknowledging an individual's speech but not its content	*Ms. Daniels has her opinion.*	Individual has been heard but no indication that the information has been accepted or validated.
Neither an individual's speech nor its content is acknowledged	A judge ignores a comment made by a family member in the courtroom.	Information from the individual is deemed not relevant or credible.
Punishment or rebuke in response to an individual	*If you speak again, I will have you removed from the courtroom.*	An individual is punished or threatened for speaking.
Asymmetric ratification	A judge acknowledges information from a caseworker but not information from the mother.	Inequality in ratifying spoken expressions of individuals.

Sources: Duranti, 2007; Lens, 2019; Philips, 2004.

Study Example: Judicial Engagement of Parents in Child Welfare Court Hearings

Decisions made by a judge, such as whether to remove a child from a home, are driven in part by information presented in court (Richards et al., 2021). Measures of judicial engagement and inquiry assess whether and how a judge addresses families and seeks information from parents in child welfare court cases (Summers et al., 2021). Summers and Gatowski (2018) examined judicial interactions as part of a study of the association between the quality of child welfare court hearings and family outcomes. The authors used data from court records collected in 2014, including 108 recordings of court hearings held across judicial districts in one state. Court case file reviews were conducted in 2017 to collect data on outcomes for families associated with the 2014 hearings. The researchers' measure of judicial engagement incorporated seven indicators of the judge's language when addressing parents. These included whether the judge addressed parents by name, asked parents if they had questions, and gave them an opportunity to speak in court. The presence of each of these judicial actions was coded dichotomously ("yes" or "no") and averaged to calculate the percentage of each engagement behavior.

Linear and logistic regression analyses were used to examine which measures of judicial engagement predicted whether a child was reunified with their family and the time to achieve permanency. Hearing quality measures were averaged both across hearings within each jurisdiction and across multiple jurisdictions. The study authors' analysis revealed an association between higher quality judicial engagement and positive child welfare outcomes. For example, when a judge referred to a mother by name, her children were more likely to achieve permanency within 12 months of initial removal. More specifically, high-quality judicial engagement predicted increased attendance by the mother at court hearings, and greater attendance by the mother predicted an increased likelihood of reunification. In addition, jurisdictions in which judges gave parents more opportunities to speak at court hearings had higher rates of child permanency within 12 months.

Analytical Methods to Study Bias

Qualitative methods have been used to study language in interactions between child welfare professionals and families and subsequent case decisions (Lens, 2019; Wayne & Smith, 2016). Although useful for understanding biased language and practice bias, studies involving qualitative methods are often constrained by small sample sizes and limited generalizability of findings. Quantitative analytic techniques involving large datasets have shown promise for detecting and measuring language and practice biases in child welfare and related human service systems. This section provides an overview of common quantitative methods and associated software programs and analytic techniques that have been used in child welfare and other fields.

Text Mining and Machine Learning

Text mining is a computer-assisted process of extracting knowledge from unstructured text documents, whereas machine learning involves the use of statistical algorithms to train a computer to classify large datasets to discern relationships among variables in the data or to predict outcomes (Murphy, 2012). Some machine learning models use hand-coded datasets to identify language patterns and to classify larger sets of textual information. An example of this approach is a study by Victor et al. (2021) that examined an initial set of summaries in child welfare investigations for the presence or absence of domestic violence services. These documents were used to develop a machine learning model to identify domestic violence service needs in a broad sample of child welfare–involved families. A more complex method is referred to as supervised machine learning, which follows a deductive approach in which a computer is trained to classify sets of manually labeled documents into a set of predetermined categories. The computer uses this information to learn a set of classification rules, which are then used to classify new unseen documents that lack the manually assigned label (Mohri et al., 2018). An example of this approach is a study by Perron and colleagues (2019), which used supervised machine learning to identify substance-related problems among families investigated for child maltreatment based on investigation summaries written by child protective service workers.

Dictionary-Based Analysis

Dictionaries are lists of predefined words or terms that reflect specific constructs of interest to researchers (Kennedy et al., 2021). Researchers may use existing dictionaries, or they may customize or develop new dictionaries to examine specific topics. An automated text search function is used to identify the frequency and location of words in the dictionary. This analytic approach assumes that each word in the dictionary has an intrinsic meaning and that its frequency of use, as well as the context in which it is used (e.g., geographic location, demographics), reflects the speakers' or writers' attitudes toward the topic or individuals being discussed (Tausczik, 2010).

Existing dictionaries. An example of a software program that includes an existing dictionary is the sentiment lexicon SentiWord, which scores each word using a positive or negative scale, with –1 representing the most negative sentiment and +1 representing the most positive sentiment. Sentiment analysis is used to identify implicit positive and negative attitudes expressed through text (Giatsoglou et al., 2017). More specifically, sentiment analysis can be used to examine bias by comparing the positive or negative tone of documents (e.g., child maltreatment reports) that refer to individuals within distinct categories such as gender or race and ethnicity. Exhibit 4 includes examples of words in the SentiWord lexicon and their associated positive or negative sentiment scores.

Exhibit 4. Word Sentiment Lexicon: SentiWords

Category	Examples of words and scores
Negative	"torture" (–.89); "murder" (–.89); "abuse" (–.87)
Positive	"happy" (+.85); "intelligent" (+.69); "safe" (+0.67)

Source: Gatti, Guerini, & Turchi, 2015.

User-defined dictionaries. Researchers may create customized dictionaries by considering specific words or terms that reflect the theoretical basis and constructs underlying a study's research focus and objectives (Kennedy et al., 2021). The word list may be informed both by prior research and expert opinion (Himmelstein et al., 2022; Sun et al., 2022). User-defined dictionaries have been employed to study how professionals use stigmatizing language. Stigmatizing language reflects elements of linguistic bias described earlier in this brief, such as noun labels (e.g., "alcoholic," "addict") and abstract language such as adjectives (e.g., "resistant," "uncooperative"), and it evokes associations that may negatively influence professional practice and judgments. For example, Goddu et al. (2018) found that, compared to neutral descriptions, patients who were described with stigmatizing language evoked negative attitudes in doctors, which in turn influenced decisions to treat pain less aggressively. Stigmatizing language is also more likely to be applied to persons who are members of marginalized racial or ethnic groups (Himmelstein et al., 2022). Examples of stigmatizing language used in studies of professional bias are shown in exhibit 5.

Exhibit 5. Stigmatizing Language in Professional Contexts

Profession or field	Examples of stigmatizing labels
Child welfare professionals	Abusive, drug user, resistant, uncooperative, unfit parent
Medical providers	Malingerer, noncompliant, pill-seeking, unmotivated, unwilling
Substance use treatment	Addict, alcoholic, junkie, substance abuser, pothead

Sources: Ashford et al., 2019; Capacity Building Center for States, 2021; Himmelstein et al., 2022.

Goodwin et al. (2022) suggested that the development of a user-defined dictionary that reflects child welfare-specific terms and concepts may be useful for identifying stigmatizing language and other forms of biased language in child welfare practice settings. The creation of such a dictionary could draw from prior work to identify buzzwords that express bias toward children and parents in child welfare cases (Agosti, 2011; Capacity Building Center for States, 2021) and could use methods from studies in healthcare settings to examine associations between stigmatizing language and disparities in professional decision making and service provision.

Future Opportunities for Research on Language Bias in Child Welfare

A lack of research contributes to the invisibility of bias. More research on spoken and written language in child welfare settings would create opportunities to identify and address biased casework practices and decisions that in turn drive disparities in outcomes (Bruster et al., 2019). Studies in healthcare settings suggest that bias erodes patient trust in providers (Cooper et al., 2012), indicating that bias may prevent the effectiveness of engagement strategies that are intended to involve and empower families in the child welfare system (Melz, 2021). Some research suggests that relationships with providers and adherence to treatment may be *more* negatively affected when providers hold subtle biases compared with those who hold more overtly racist attitudes (Hagiwara et al., 2013). Consequently, practices and services that are intended to help families may in fact harm them when they are associated with bias.

Bias may be subtle, but it can be detected and measured. Sue et al. (2007) suggested that the challenge of quantifying and measuring subtle biases (e.g., microaggressions) has led researchers to avoid its study, despite research demonstrating the significant harm these forms of bias can inflict. Despite the challenges, researchers have developed and operationalized tools to measure bias constructs. Some methods have been developed in partnership with individuals who are the targets of bias. For example, Breitfeller et al. (2019) asked individuals who use a social media website (Reddit) to categorize examples of microaggressions based on a typology developed by Sue et al. (2007), and then used a supervised machine learning process to better identify examples and the targets of online microaggressions.

Studies of language bias can use and build on existing research methods, tools, and data sources. Examples of relevant information sources and practice indicators include the use of surnames to acknowledge individuality and convey respect (Wood & Gonda, 2014) and generic labels such as “the mother” that may evoke stereotypical expectations (Lens, 2019). More recently, the Understanding Judicial Decision-Making and Hearing Quality in Child Welfare project (Administration for Children and Families [ACF], 2022) is developing a list of stigmatizing terms to identify and measure bias in child welfare court case files. See exhibit 5 for examples of stigmatizing language.

Dictionary-based analytic methods could make more intensive use of child welfare administrative datasets, which Perron et al. (2019) described as one of the largest untapped information sources created and managed by child welfare agencies. Henry et al. (2014) noted that these data sources are nonintrusive and can be applied to specific types of casework involving diverse groups of families. Familiarity with child welfare processes, and with the forms and tools used to collect child welfare data, is important because they drive the content and focus of information collection (Goodwin et al., 2022). Recent research involving the textual analysis of child welfare administrative data has focused on detecting family issues such as parental substance use (Perron et al., 2019) and domestic violence (Victor et al., 2021) and on interactions with reporters of suspected maltreatment (Goodwin et al., 2022). Many

Current Study of Professional Bias in Child Welfare

The Understanding Judicial Decision-Making and Hearing Quality in Child Welfare project (ACF, 2022) is exploring, in part, how language used during initial child welfare hearings and in court case files may include stigmatizing terms and indicate bias. The study will count the terms used, document to whom they refer (e.g., mother, father, child), and explore whether terms are applied more frequently to families of different races and ethnicities.

The study is being conducted by James Bell Associates, the American Bar Association Center on Children and the Law, and Co-Principal Investigators Drs. Alicia Summers and Sophia Gatowski. It is funded by the Office of Planning, Research, and Evaluation and the Children’s Bureau in the Administration for Children and Families, U.S. Department of Health and Human Services.

opportunities remain to use administrative data sources to shed light on language and decision making in the context of child welfare staff practice.

Improved understanding of biased language can contribute to more effective practices to address disparities in the child welfare system. Current practice initiatives, such as efforts to engage families in case planning and decision making (Melz, 2021) and to encourage caseworkers to reflect on their own potential biases before making important case decisions (Russell & Summers, 2013), could be evaluated using language bias constructs and measures. These evaluations could assess changes in bias, the effects of bias on interactions with children and families, and longer-term impacts of bias on safety, permanency, and well-being outcomes.

Language bias remains a largely unexplored but important subject of inquiry in the child welfare field that can build on the concepts, tools, and methods summarized in this brief. Research in this area has the potential to address the ongoing problem of bias in case practice and decision making and to improve the longstanding patterns of disproportionate representation of vulnerable families (particularly BIPOC families and those in other marginalized groups) in the child welfare system and the disparate outcomes they often experience.

"Researchers continue to omit subtle racism and microaggressions from their research, and this absence conveys the notion that covert forms of racism are not as valid or as important as racist events that can be quantified and 'proven.'"

—Sue et al., 2007, p. 283

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