# Online Appendix

## WHAT WE TEACH ABOUT RACE AND GENDER: REPRESENTATION IN IMAGES AND TEXT OF CHILDREN'S BOOKS*

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# Online Appendix

## Table of Contents

# A Appendix Tables

TABLE AI
Purchaser Demographics of Children's Book Purchases in Numerator Data

| | *All Children's Books* | | *Award-Winning Children's Books* | |
|---|---|---|---|---|
| | N | Mean | N | Mean |
| *Purchaser Demographics* | (1) | (2) | (3) | (4) |
| **Children** | | | | |
| Has Children | 1,547,044 | 0.73 | 62,283 | 0.70 |
| Has Children Ages 0-5 | 1,188,039 | 0.23 | 47,782 | 0.14 |
| Has Children Ages 6-12 | 1,188,039 | 0.46 | 47,782 | 0.38 |
| Has Children Ages 13-17 | 1,188,039 | 0.23 | 47,782 | 0.35 |
| **Race/Ethnicity** | | | | |
| Asian | 1,506,152 | 0.06 | 60,633 | 0.06 |
| Black | 1,506,152 | 0.04 | 60,633 | 0.07 |
| Latinx | 1,506,152 | 0.06 | 60,633 | 0.08 |
| White | 1,506,152 | 0.81 | 60,633 | 0.75 |
| Other | 1,506,152 | 0.03 | 60,633 | 0.03 |
| **Gender** | | | | |
| Female | 1,534,051 | 0.89 | 61,714 | 0.88 |
| Male | 1,534,051 | 0.10 | 61,714 | 0.11 |
| Other | 1,534,051 | 0.01 | 61,714 | 0.01 |
| **Sexuality** | | | | |
| Gay/Lesbian | 1,111,247 | 0.01 | 41,943 | 0.02 |
| Straight | 1,111,247 | 0.82 | 41,943 | 0.81 |
| Bisexual | 1,111,247 | 0.03 | 41,943 | 0.03 |
| Other Sexuality | 1,111,247 | 0.01 | 41,943 | 0.01 |
| Prefer Not to Answer | 1,111,247 | 0.13 | 41,943 | 0.14 |
| **Income** | | | | |
| High Income | 1,539,767 | 0.49 | 62,031 | 0.51 |
| Mid Income | 1,539,767 | 0.31 | 62,031 | 0.30 |
| Low Income | 1,539,767 | 0.20 | 62,031 | 0.19 |
| **Education** | | | | |
| Advanced Education | 1,548,085 | 0.25 | 62,345 | 0.31 |
| College Education | 1,548,085 | 0.62 | 62,345 | 0.58 |
| High School Education | 1,548,085 | 0.12 | 62,345 | 0.09 |
| Less than High School | 1,548,085 | 0.02 | 62,345 | 0.02 |

*Note:* This table shows the sample size and mean of purchaser demographics for children's book purchases in Numerator OmniPanel data from 2017-2020. The first two columns include all children's book purchases. The last two columns include all purchases of a children's book which was recognized by one of the awards in our sample. The majority of the books in this panel were purchased on Amazon (88%), with Walmart (3%) and Target (3%) as the next most popular retailers.

TABLE AII

A Short Bibliography of Relevant Manual Content Analysis Work

| First author surname (1) | Year (2) | Journal (3) | Title (4) |
|---|---|---|---|
| Weitzman | 1972 | American Journal of Sociology | Sex-role socialization in picture books for preschool children |
| Kolbe | 1981 | Social Psychology Quarterly | Sex-role stereotyping in preschool children's picturebooks |
| Davis | 1984 | Sex Roles | Sex-differentiated behaviors in nonsexist picture books |
| Williams | 1987 | Social Science Quarterly | Sex role socialization in picturebooks: An update |
| McDonald | 1989 | Journal of Genetic Psychology | Sex bias in the representation of male and female characters in children's picture books |
| Allen | 1993 | Journal of Research in Childhood Education | Changes in sex role stereotyping in Caldecott Medal award picture books 1938-1988 |
| Clark | 1993 | Gender & Society | Of Caldecotts and kings: Gendered images in recent American children's books by Black and non-Black illustrators |
| Dellmann-Jenkins | 1993 | Journal of Research in Childhood Education | Sex roles and cultural diversity in recent award winning picture books for young children |
| Kortenhouse | 1993 | Sex Roles | Gender role stereotyping in children's literature: An update |
| Tepper | 1999 | Sex Roles | Gender differences in emotional language in children's picture books |
| Clark | 2003 | Sex Roles | Two steps forward, one step back: The presence of female characters and gender stereotyping in award-winning picture books between the 1930s and the 1960s |
| Hamilton | 2006 | Sex Roles | Gender stereotyping and under-representation of female characters in 200 popular children's picture books: A twenty-first century update |
| Crisp | 2011 | Journal of Children's Literature | Telling tales about gender: A critical analysis of Caldecott Medal-winning picturebooks, 1938-2011 |
| McCabe | 2011 | Gender & Society | Gender in twentieth-century children's books: Patterns of disparity in titles and central characters |
| Koss | 2015 | Journal of Children's Literature | Diversity in contemporary picturebooks: A content analysis |
| Koss | 2016 | The Reading Teacher | Meeting characters in Caldecotts: What does this mean for today's readers? |
| Koss | 2018 | Journal of Children's Literature | Mapping the diversity in Caldecott books from 1938 to 2017: The changing topography |

*Note:* This table provides a bibliographic list of scholarship in the field of manual content analysis from which we drew in our study. We note that this list gives only those studies we read and were in direct dialogue with. We stress that it is not meant as a total catalogue of manual content analysis of these issues; rather, we offer it as acknowledging a broader set of papers than we had space to describe in the body of the manuscript, and from which we learned in the crafting of this study. We also hope that it can serve as a jumping-off point for those interested in exploring this literature further.

TABLE AIII
Differences in Skin Color by Age and Gender

| | *Dependent variable: Skin Tint* | | | | | | |
|---|---|---|---|---|---|---|---|
| | All | Mainstream | Mainstream | Mainstream | Diversity | Diversity | Diversity |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Diversity | $-10.350^{***}$ | | | | | | |
| | (0.298) | | | | | | |
| Child | $5.769^{***}$ | $5.531^{***}$ | | | $6.195^{***}$ | | |
| | (0.274) | (0.436) | | | (0.348) | | |
| Male | $-1.394^{***}$ | | $-0.076$ | | | $-2.501^{***}$ | |
| | (0.207) | | (0.359) | | | (0.254) | |
| Female Adult | | | | $-5.939^{***}$ | | | $-5.015^{***}$ |
| | | | | (0.652) | | | (0.516) |
| Male Adult | | | | $-5.942^{***}$ | | | $-7.759^{***}$ |
| | | | | (0.654) | | | (0.510) |
| Female Child | | | | $-0.721$ | | | $-0.541$ |
| | | | | (0.780) | | | (0.642) |
| Decade | $0.028^{***}$ | $-0.027^{***}$ | $-0.021^{***}$ | $-0.027^{***}$ | $0.210^{***}$ | $0.215^{***}$ | $0.214^{***}$ |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.011) | (0.011) | (0.011) |
| Constant | 4.519 | $111.039^{***}$ | $100.906^{***}$ | $116.495^{***}$ | $-371.641^{***}$ | $-378.888^{***}$ | $-373.547^{***}$ |
| | (10.711) | (11.887) | (11.935) | (11.925) | (22.845) | (22.929) | (22.828) |
| Observations | 44,606 | 14,173 | 14,173 | 14,173 | 30,433 | 30,433 | 30,433 |
| Adjusted $R^2$ | 0.052 | 0.012 | 0.001 | 0.012 | 0.021 | 0.014 | 0.024 |

*Note:* The table shows regressions of a face's skin tint on indicator variables indicating a face's race/gender and an indicator variable indicating whether the face belongs to a book in the Diversity collection. The first column includes all faces in the Mainstream and Diversity collections. Columns 2-4 include only faces found in the Mainstream collection, and columns 5-7 include only faces found in the Diversity collection.
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

TABLE AIV

Top Five Most Mentioned Famous People, by Collection

| Collection | Rank | Name | Race | Gender | Mentions | Books |
|---|---|---|---|---|---|---|
| Mainstream | 1 | George Washington | White | Male | 152 | 32 |
| Mainstream | 2 | Abraham Lincoln | White | Male | 270 | 25 |
| Mainstream | 3 | Thomas Jefferson | White | Male | 71 | 15 |
| Mainstream | 4 | John Adams | White | Male | 60 | 14 |
| Mainstream | 5 | Benjamin Franklin | White | Male | 23 | 12 |
| Diversity | 1 | Martin Luther King Junior | Black | Male | 282 | 51 |
| Diversity | 2 | Abraham Lincoln | White | Male | 72 | 41 |
| Diversity | 3 | George Washington | White | Male | 62 | 40 |
| Diversity | 4 | Frederick Douglass | Black | Male | 131 | 30 |
| Diversity | 5 | Langston Hughes | Black | Male | 109 | 30 |
| People of Color | 1 | Martin Luther King Junior | Black | Male | 263 | 48 |
| People of Color | 2 | Abraham Lincoln | White | Male | 70 | 39 |
| People of Color | 3 | George Washington | White | Male | 58 | 37 |
| People of Color | 4 | Frederick Douglass | Black | Male | 131 | 30 |
| People of Color | 5 | Langston Hughes | Black | Male | 108 | 29 |
| African American | 1 | Langston Hughes | Black | Male | 53 | 17 |
| African American | 2 | Martin Luther King Junior | Black | Male | 130 | 16 |
| African American | 3 | Malcolm X | Black | Male | 69 | 12 |
| African American | 4 | Frederick Douglass | Black | Male | 43 | 12 |
| African American | 5 | Duke Ellington | Black | Male | 25 | 12 |
| Ability | 1 | Harold Pinter | White | Male | 78 | 2 |
| Ability | 2 | Andy Warhol | White | Male | 4 | 2 |
| Ability | 3 | Marco Polo | White | Male | 3 | 2 |
| Ability | 4 | Duke Ellington | Black | Male | 2 | 2 |
| Ability | 5 | Judy Blume | White | Female | 2 | 2 |
| Female | 1 | John F. Kennedy | White | Male | 8 | 4 |
| Female | 2 | Martin Luther King Junior | Black | Male | 19 | 3 |
| Female | 3 | Jimmy Carter | White | Male | 15 | 3 |
| Female | 4 | Betty Friedan | White | Female | 10 | 3 |
| Female | 5 | Richard Nixon | White | Male | 9 | 3 |
| LGBTQIA+ | 1 | Alicia Keys | Multiracial | Female | 3 | 3 |
| LGBTQIA+ | 2 | Britney Spears | White | Female | 3 | 3 |
| LGBTQIA+ | 3 | Marilyn Monroe | White | Female | 3 | 3 |
| LGBTQIA+ | 4 | Julia Roberts | White | Female | 5 | 2 |
| LGBTQIA+ | 5 | Alexander Hamilton | White | Male | 4 | 2 |

*Note:* This table shows the five most frequently mentioned famous people in each collection, along with their race, their gender, the number of times they were mentioned, and the number of books in which they appeared.

TABLE AV

Top Five Most Mentioned Famous Females, by Collection

| Collection | Rank | Name | Race | Mentions | Books |
|---|---|---|---|---|---|
| Mainstream | 1 | Eleanor Roosevelt | White | 30 | 7 |
| Mainstream | 2 | Martha Washington | White | 9 | 6 |
| Mainstream | 3 | Emily Dickinson | White | 7 | 6 |
| Mainstream | 4 | Shirley Temple | White | 12 | 5 |
| Mainstream | 5 | Rosa Parks | Black | 43 | 4 |
| Diversity | 1 | Rosa Parks | Black | 157 | 27 |
| Diversity | 2 | Harriet Tubman | Black | 35 | 19 |
| Diversity | 3 | Eleanor Roosevelt | White | 42 | 18 |
| Diversity | 4 | Coretta Scott King | Black | 23 | 15 |
| Diversity | 5 | Lena Horne | White | 20 | 14 |
| People of Color | 1 | Rosa Parks | Black | 152 | 25 |
| People of Color | 2 | Harriet Tubman | Black | 35 | 19 |
| People of Color | 3 | Eleanor Roosevelt | White | 41 | 17 |
| People of Color | 4 | Coretta Scott King | Black | 22 | 14 |
| People of Color | 5 | Lena Horne | White | 20 | 14 |
| African American | 1 | Rosa Parks | Black | 44 | 11 |
| African American | 2 | Coretta Scott King | Black | 12 | 10 |
| African American | 3 | Zora Neale Hurston | Black | 21 | 9 |
| African American | 4 | Lena Horne | White | 14 | 9 |
| African American | 5 | Harriet Tubman | Black | 13 | 9 |
| Ability | 1 | Judy Blume | White | 2 | 2 |
| Ability | 2 | Shirley Temple | White | 12 | 1 |
| Ability | 3 | Anna Lee | White | 4 | 1 |
| Ability | 4 | Avril Lavigne | White | 4 | 1 |
| Ability | 5 | Marilyn Vos Savant | White | 4 | 1 |
| Female | 1 | Betty Friedan | White | 10 | 3 |
| Female | 2 | Mary Pickford | White | 5 | 3 |
| Female | 3 | Billie Jean King | White | 24 | 2 |
| Female | 4 | Katharine Graham | White | 14 | 2 |
| Female | 5 | Gloria Steinem | White | 13 | 2 |
| LGBTQIA+ | 1 | Alicia Keys | Multiracial | 3 | 3 |
| LGBTQIA+ | 2 | Britney Spears | White | 3 | 3 |
| LGBTQIA+ | 3 | Marilyn Monroe | White | 3 | 3 |
| LGBTQIA+ | 4 | Julia Roberts | White | 5 | 2 |
| LGBTQIA+ | 5 | Patsy Cline | White | 3 | 2 |

*Note:* In this table, we show the five most frequently mentioned famous females in each collection, along with their race, the number of times they were mentioned, and the number of books in which they appeared.

TABLE AVI
Top Five Most Mentioned Famous Males, by Collection

| Collection | Rank | Name | Race | Mentions | Books |
|---|---|---|---|---|---|
| Mainstream | 1 | George Washington | White | 152 | 32 |
| Mainstream | 2 | Abraham Lincoln | White | 270 | 25 |
| Mainstream | 3 | Thomas Jefferson | White | 71 | 15 |
| Mainstream | 4 | John Adams | White | 60 | 14 |
| Mainstream | 5 | Benjamin Franklin | White | 23 | 12 |
| Diversity | 1 | Martin Luther King Junior | Black | 282 | 51 |
| Diversity | 2 | Abraham Lincoln | White | 72 | 41 |
| Diversity | 3 | George Washington | White | 62 | 40 |
| Diversity | 4 | Frederick Douglass | Black | 131 | 30 |
| Diversity | 5 | Langston Hughes | Black | 109 | 30 |
| People of Color | 1 | Martin Luther King Junior | Black | 263 | 48 |
| People of Color | 2 | Abraham Lincoln | White | 70 | 39 |
| People of Color | 3 | George Washington | White | 58 | 37 |
| People of Color | 4 | Frederick Douglass | Black | 131 | 30 |
| People of Color | 5 | Langston Hughes | Black | 108 | 29 |
| African American | 1 | Langston Hughes | Black | 53 | 17 |
| African American | 2 | Martin Luther King Junior | Black | 130 | 16 |
| African American | 3 | Malcolm X | Black | 69 | 12 |
| African American | 4 | Frederick Douglass | Black | 43 | 12 |
| African American | 5 | Duke Ellington | Black | 25 | 12 |
| Ability | 1 | Harold Pinter | White | 78 | 2 |
| Ability | 2 | Andy Warhol | White | 4 | 2 |
| Ability | 3 | Marco Polo | White | 3 | 2 |
| Ability | 4 | Duke Ellington | Black | 2 | 2 |
| Ability | 5 | Mark Twain | White | 2 | 2 |
| Female | 1 | John F. Kennedy | White | 8 | 4 |
| Female | 2 | Martin Luther King Junior | Black | 19 | 3 |
| Female | 3 | Jimmy Carter | White | 15 | 3 |
| Female | 4 | Richard Nixon | White | 9 | 3 |
| Female | 5 | Barack Obama | Black | 5 | 3 |
| LGBTQIA+ | 1 | Alexander Hamilton | White | 4 | 2 |
| LGBTQIA+ | 2 | Adam Lambert | White | 3 | 2 |
| LGBTQIA+ | 3 | Alice Cooper | White | 3 | 2 |
| LGBTQIA+ | 4 | James Dean | White | 3 | 2 |
| LGBTQIA+ | 5 | Michael Jackson | Black | 3 | 2 |

*Note:* In this table, we show the five most frequently mentioned famous males in each collection, along with their race, the number of times they were mentioned, and the number of books in which they appeared.

# TABLE AVII
## Top Mentioned Famous Person, by Collection and Decade

| Decade<br>(1) | Mainstream<br>(2) | Diversity<br>(3) | People of Color<br>(4) | African American<br>(5) | Ability<br>(6) | Female<br>(7) | LGBTQ<br>(8) |
|---|---|---|---|---|---|---|---|
| 1920 | James Fenimore Cooper<br>*White Male*<br>Charles Darwin<br>*White Male*<br>Mark Twain<br>*White Male* | | | | | | |
| 1930 | Abraham Lincoln<br>*White Male* | | | | | | |
| 1940 | Benjamin Franklin<br>*White Male* | | | | | | |
| 1950 | George Washington<br>*White Male* | | | | | | |
| 1960 | George Washington<br>*White Male* | | | | | | |
| 1970 | Claude Lorrain<br>*White Male*<br>Leonardo da Vinci<br>*White Male* | Frederick Douglass<br>*Black Male* | Frederick Douglass<br>*Black Male* | Frederick Douglass<br>*Black Male* | | | |
| 1980 | George Washington<br>*White Male* | Franklin D. Roosevelt<br>*White Male* | Franklin D. Roosevelt<br>*White Male* | Paul Robeson<br>*Black Male* | | | |
| 1990 | William Shakespeare<br>*White Male* | Martin Luther King Jr.<br>*Black Male* | Martin Luther King Jr.<br>*Black Male* | Martin Luther King Jr.<br>*Black Male* | | | |
| 2000 | Martin Luther King Jr.<br>*Black Male* | George Washington<br>*White Male* | George Washington<br>*White Male* | Langston Hughes<br>*Black Male* | Judy Blume<br>*White Female* | | |
| 2010 | George Washington<br>*White Male* | Martin Luther King Jr.<br>*Black Male* | Martin Luther King Jr.<br>*Black Male* | Malcolm X<br>*Black Male* | Andy Warhol<br>*White Male* | John F. Kennedy<br>*White Male* | Alicia Keys<br>*Multiracial Female*<br>Marilyn Monroe<br>*White Female*<br>Britney Spears<br>*White Female* |

*Note:* In this table, we show the top most uniquely mentioned (that is, mentioned in the largest number of books) famous figure in each collection by decade. When multiple names are listed for a collection within the same decade, it indicates that each of those people were tied for the most uniquely mentioned famous person in that collection-by-decade.

TABLE AVIII
Award-winning Book Purchases by Award Type and Purchaser Identity

| | *Dependent variable: Purchases of books in collection* | | | | | |
|---|---|---|---|---|---|---|
| | Female | LGBTQIA+ | African American | Asian | Latinx | Mainstream |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Male | $-0.008^{**}$ | | | | | $-0.011$ |
| | (0.003) | | | | | (0.008) |
| Other (Gender) | $0.020^{*}$ | | | | | 0.005 |
| | (0.011) | | | | | (0.024) |
| LGBTQIA+ | | $0.032^{***}$ | | | | $-0.084^{***}$ |
| | | (0.004) | | | | (0.011) |
| Prefer not to Answer (Sexuality) | | 0.001 | | | | 0.001 |
| | | (0.003) | | | | (0.007) |
| Asian | | | 0.009 | $0.005^{**}$ | 0.003 | $-0.017^{*}$ |
| | | | (0.005) | (0.002) | (0.003) | (0.010) |
| Black | | | $0.219^{***}$ | $-0.002$ | 0.004 | $-0.165^{***}$ |
| | | | (0.005) | (0.002) | (0.003) | (0.010) |
| Latinx | | | $0.024^{***}$ | 0.001 | $0.088^{***}$ | $-0.104^{***}$ |
| | | | (0.005) | (0.002) | (0.003) | (0.009) |
| Other (Race) | | | $0.049^{***}$ | $-0.002$ | $0.014^{***}$ | $-0.041^{***}$ |
| | | | (0.008) | (0.003) | (0.005) | (0.014) |
| Constant | $0.068^{***}$ | $0.043^{***}$ | $0.101^{***}$ | $0.014^{***}$ | $0.036^{***}$ | $0.583^{***}$ |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.003) |
| Observations | 61,714 | 41,943 | 60,633 | 60,633 | 60,633 | 40,773 |
| Adjusted $R^2$ | 0.0001 | 0.001 | 0.030 | 0.0001 | 0.013 | 0.011 |

*Note:* In this table, we estimate whether individuals purchasing award-winning children's books are more likely to purchase a book recognized for highlighting one of their own identities. In each column, we report results from regressing the likelihood of the purchase of a book belonging to a given collection on purchaser identity traits pertaining to that collection. These collections are listed in the column headers; our categorization of awards into collections appears in Appendix Figure BIa. Two collections are unique to this table: for the Asian collection, we include the Arab American, Asian/Pacific American, Middle East, and South Asia awards; for the Latinx collection, we include the Américas, Pura Belpré, and Tomás Rivera Mexican American awards. We describe the awards in Appendix D. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

TABLE AIX

Correlation between U.S. Demographics and Representation

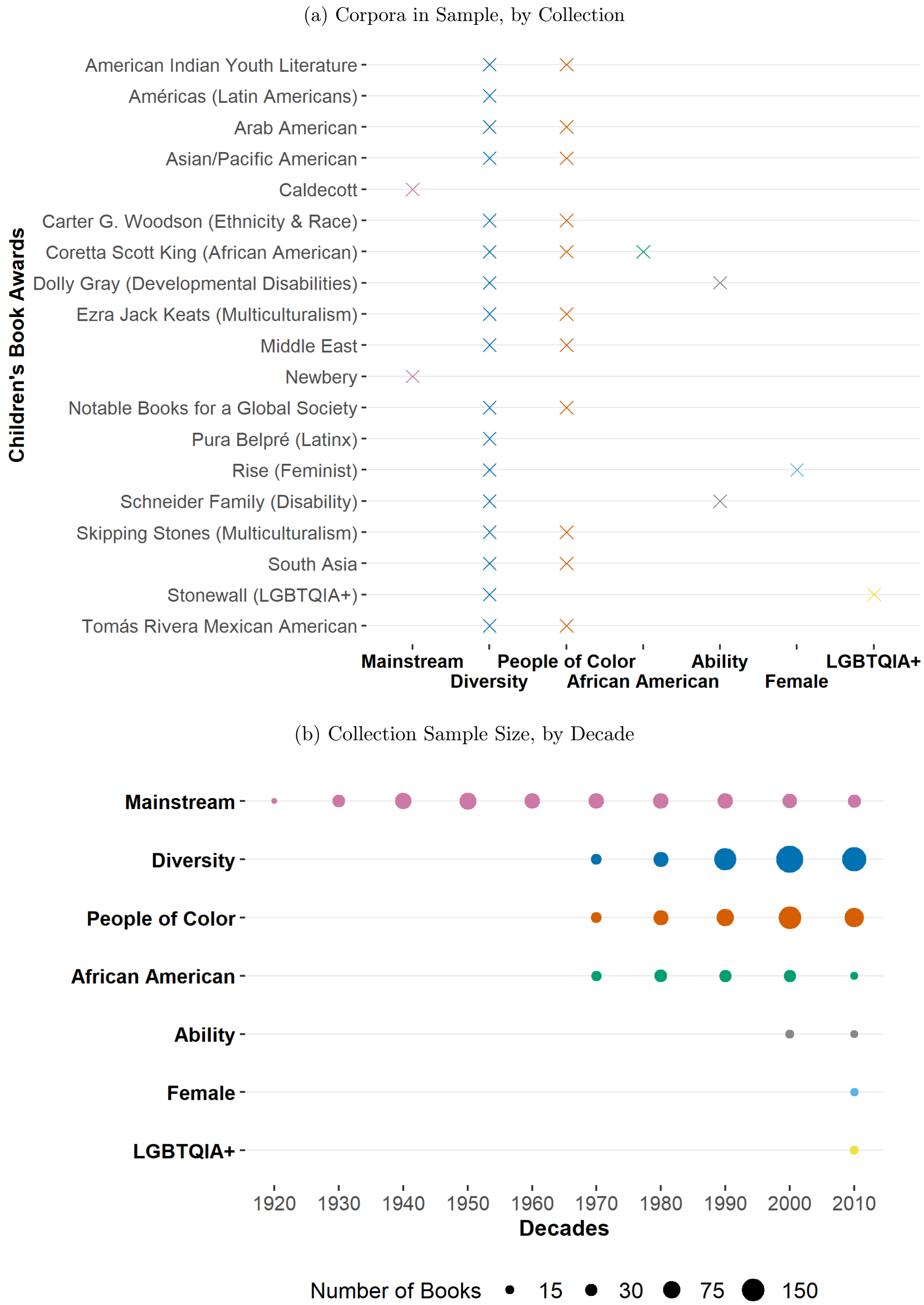
| | *Dependent variable: Percent of* | | | |
|---|---|---|---|---|
| | Faces | Famous People | Female Words | Images vs. Text |
| | (1) | (2) | (3) | (4) |
| *Panel A: Percent of Labor Force Participation* | | | | |
| Females | -0.08 | 0.69** | 0.45*** | -0.36 |
| | (0.15) | (0.29) | (0.15) | (0.22) |
| *Panel B: Percent of Population* | | | | |
| Asian | 1.49** | -0.89 | | |
| | (0.5) | (0.73) | | |
| Black | 1.49*** | 5.15*** | | |
| | (0.25) | (1.36) | | |
| Latinx | -0.53 | 0.03 | | |
| | (0.21) | (0.05) | | |
| White | 0.40** | 0.33 | | |
| | (0.16) | (0.24) | | |

*Note:* This table estimates the relationship between major demographic parameters (U.S. female labor force participation in Panel A and the racial composition of the U.S. population in Panel B) and representation in the images and text of children's books from our Mainstream collection. We regress a measure of market share or market power – either population share of a given racial group or female labor force participation – for a given race or gender on a measure of their proportional representation in award-winning children's books over time. We show each coefficient from these bivariate regressions in this table, with standard errors in parentheses. For example, the first row and column shows the coefficient from a regression of the percentage of female labor force participation on the percentage of female faces in the Mainstream collection over time. Our data on female labor force participation is constructed by taking the yearly average over monthly unadjusted data between 1948-2019 from the U.S. Bureau of Labor Statistics and retrieved from FRED, Federal Reserve Bank of St. Louis. Our data on population breakdown by race is from 1920-2019 U.S. census data. Census information on the proportion of people who are Latinx comes from a response to a question regarding ethnicity and is not mutually exclusive to the other race categories. We construct each race/ethnicity category to be mutually exclusive; for example, we count an individual who identifies as Latinx and White in the Latinx category, not the White category. Census data on ethnicity are only available beginning in 1970.

*p<0.1; **p<0.05; ***p<0.01

# B Appendix Figures

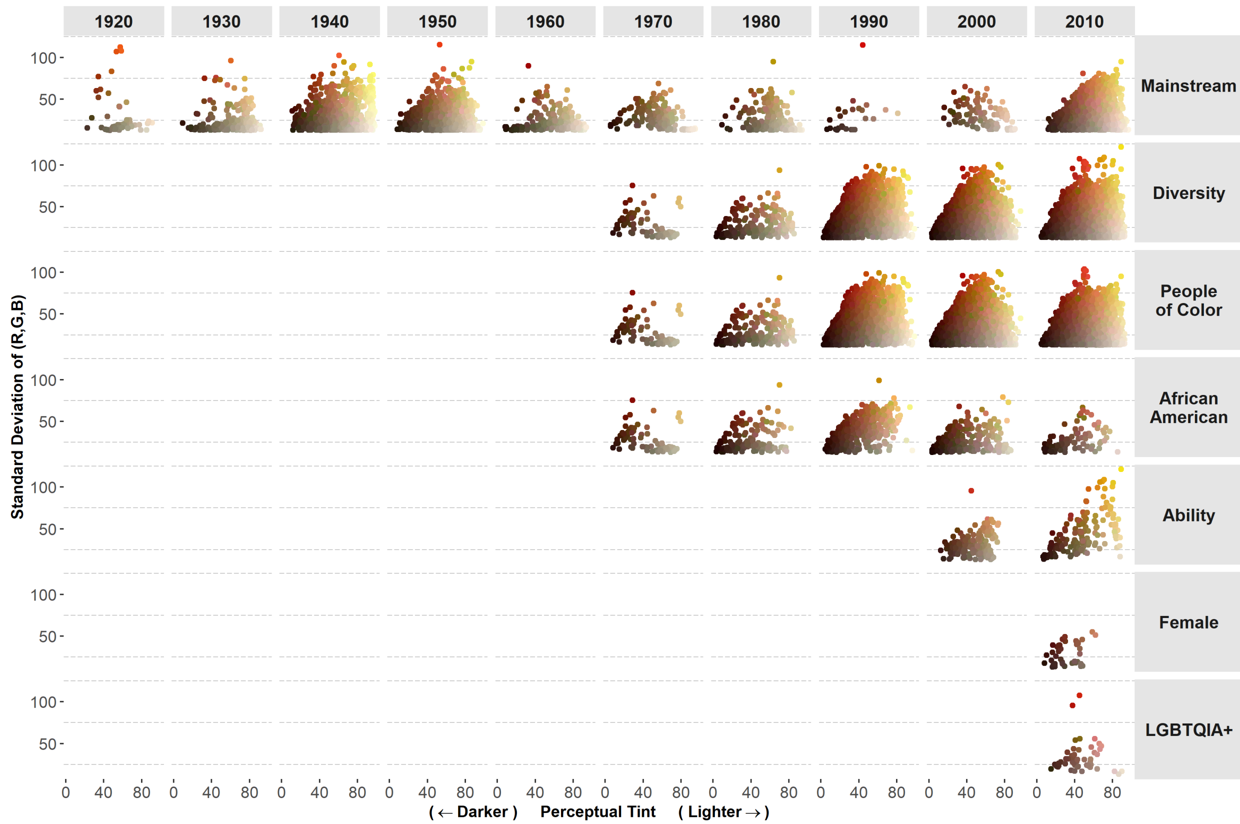
FIGURE BI
Books in the Sample




*Note:* This figure shows the main sources of data we use for our analysis. In Panel A, we list the book awards in our sample, along with the collections into which we group them in our analysis. In Panel B, we show our sample size in each collection, over time.

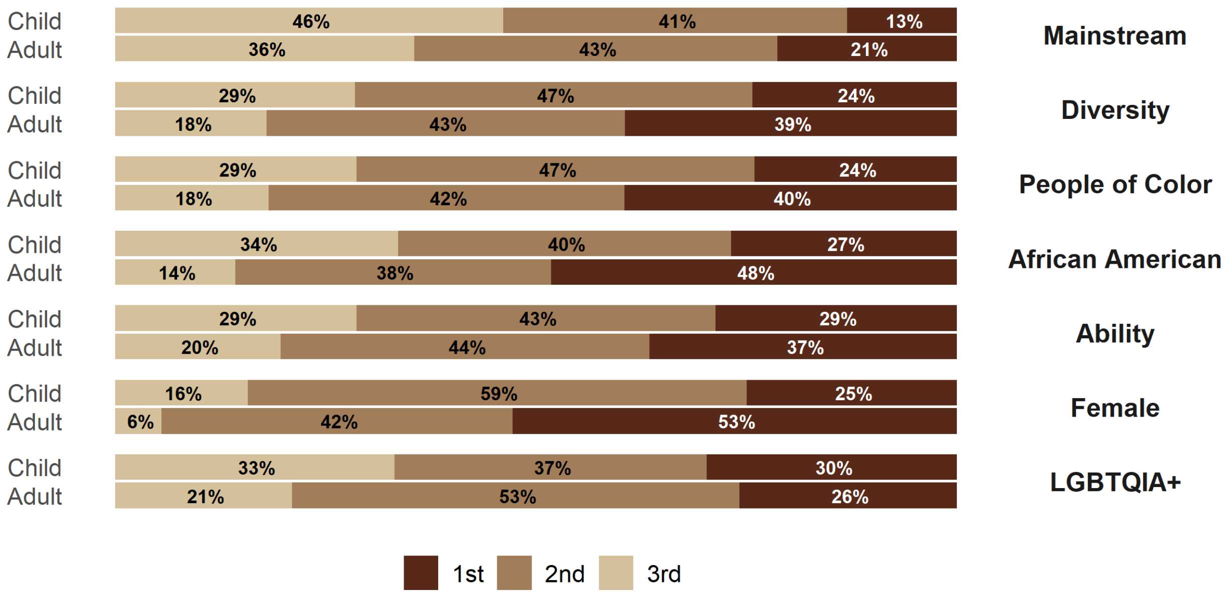
FIGURE BII

Skin Color Data Over Time, Human Skin Colors




*Note:* In this figure, we show the representative skin colors for all detected faces with human skin colors (polychromatic skin colors where R $\geq$ G $\geq$ B) in each collection-by-decade cell. As described in Section IV.A, we use our face detection model (FDAI) trained on illustrations to classify faces in images. We determine a face's representative skin color using methods described in Section IV.A.2.

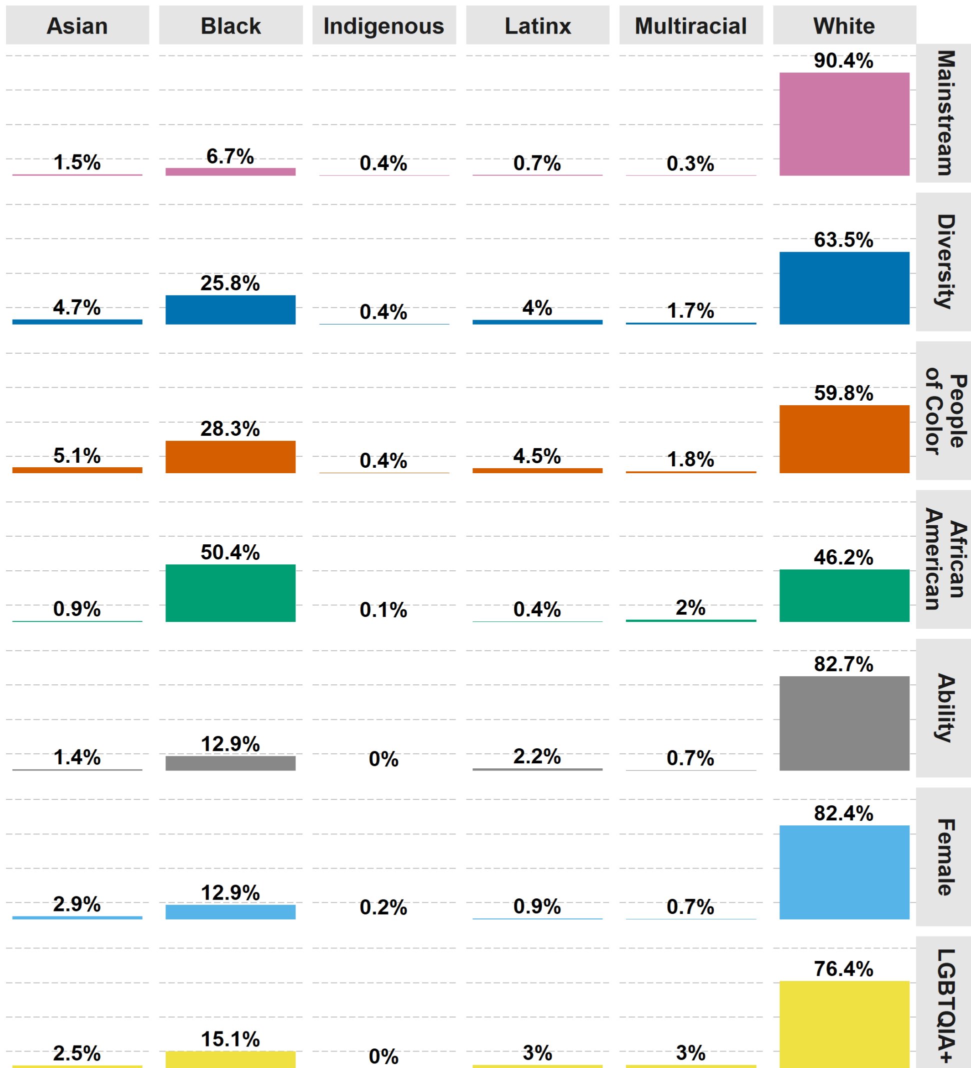
FIGURE BIII
Skin Color Terciles by Age, by Collection




*Note:* In this figure, we show the proportion of faces in each tercile of the perceptual tint distribution by the classified age (adult vs. child) of the face. We detect faces using our face detection model (FDAI). Within these faces, we classify age using an AutoML algorithm we trained using the UTKFace public data set. Skin tint is determined by the $L^*$ value of a face's representative skin color in L*a*b* space. These figures show the results for images that have human skin colors (defined as polychromatic colors where $R \geq G \geq B$).

FIGURE BIV

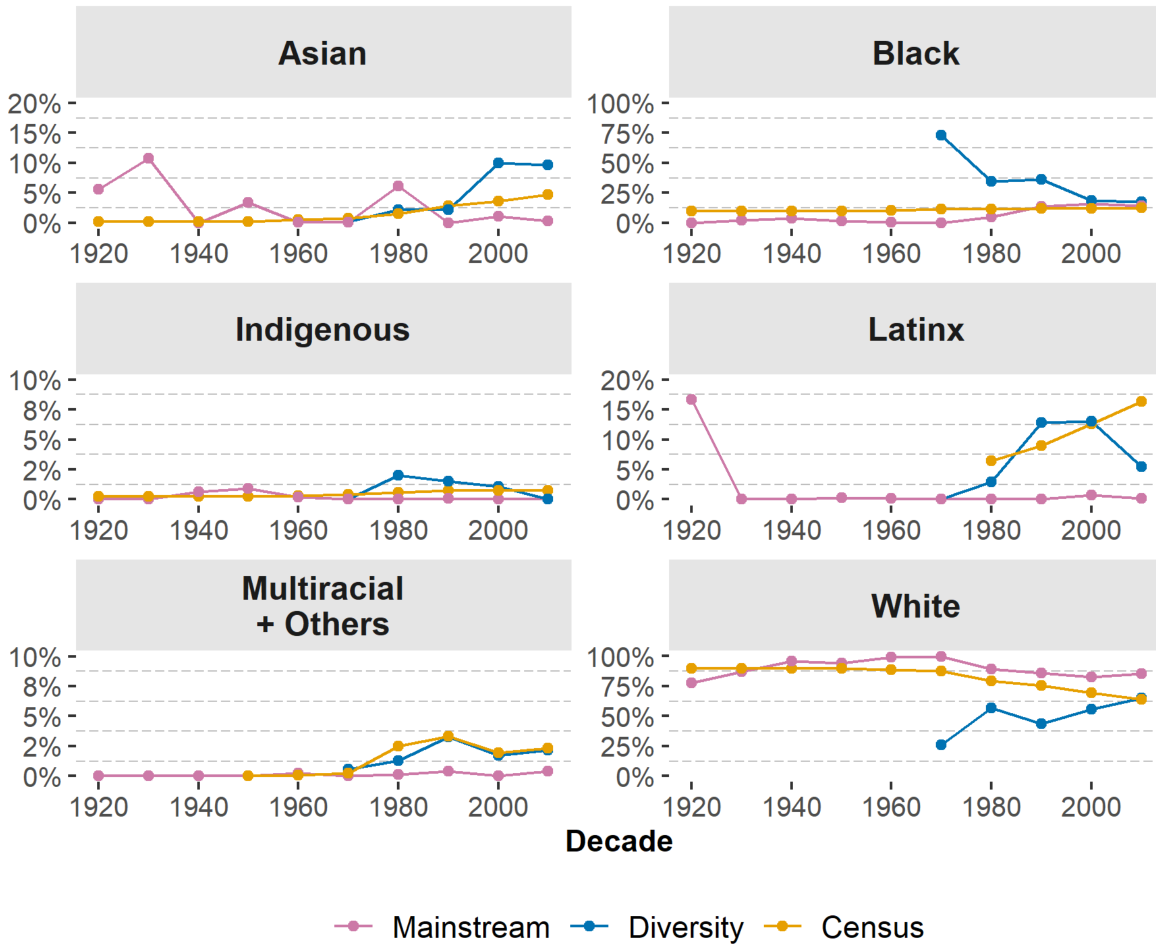
Race Classifications of Famous Figures in the Text




*Note:* In this figure, we count the number of famous people mentioned at least once in a given book and sum over all books in a collection. We then show the percentage breakdown of these famous people by race. For example, if Aretha Franklin was uniquely mentioned in 3 different books within a collection and Jimmy Carter is uniquely mentioned in 2 books within the same collection (and if these were the only famous individuals mentioned), then 60 percent of the unique famous people mentioned in that collection would be Black. In Table I, we find the proportion of uniquely mentioned famous people in each racial category for each book and report the average across all books in collection. We identify famous individuals using methods described in Section IV.B. We collapse the following identities: East Asian, Middle Eastern, and South Asian into the Asian category; North American Indigenous peoples and South American Indigenous peoples into the Indigenous category; and African American and Black African into the Black category. If an individual was coded as having more than one race, we classify them as multiracial.

FIGURE BV

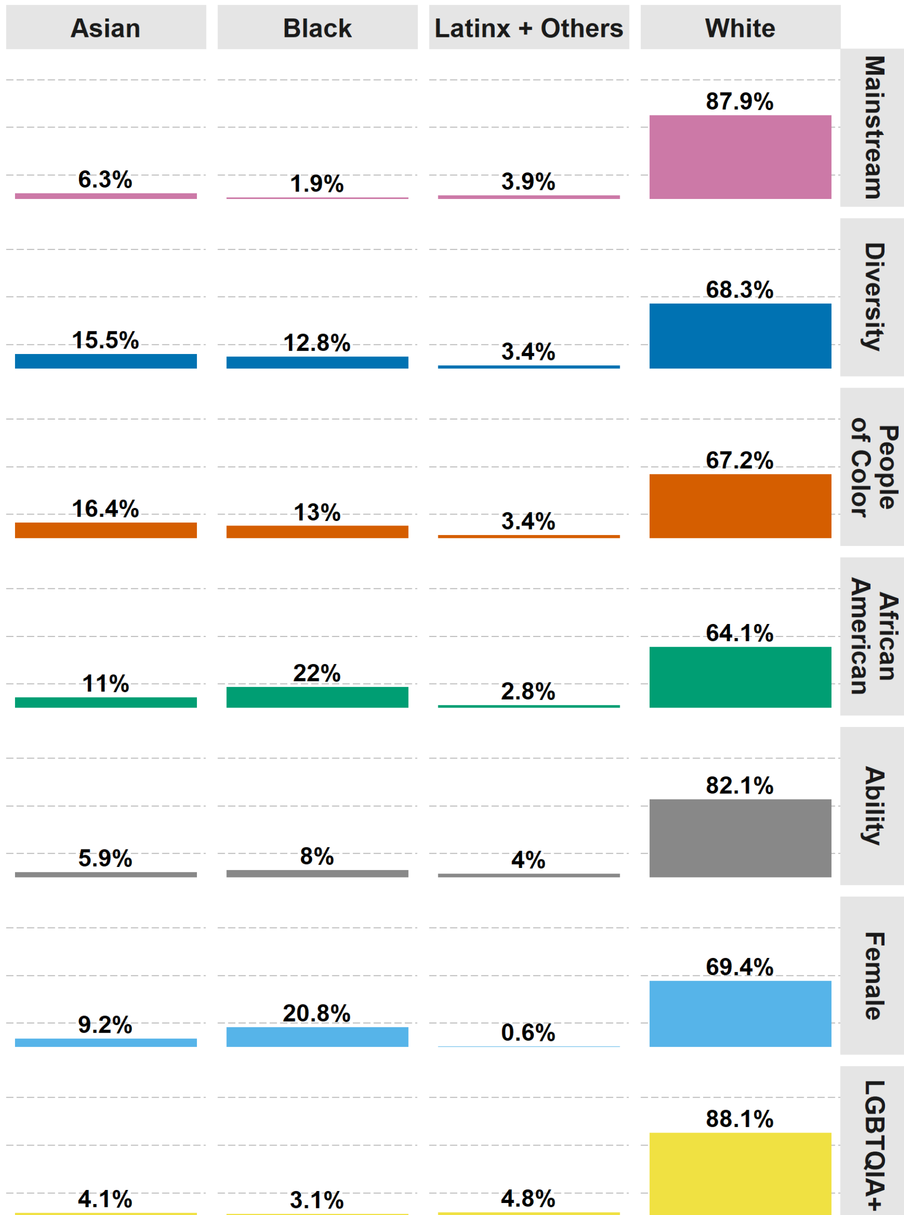
Share of U.S. Population and Famous People in the Text, by Race/Ethnicity




*Note:* In this figure, we show the percent breakdown of famous people mentioned in a given book by race/ethnicity. For example, if Aretha Franklin was mentioned 3 times in a book and Jimmy Carter is mentioned 2 times (and if these were the only famous individuals mentioned), then 60 percent of the mentions of famous people in that book would be Black. We then show the average percentage breakdown over all books by collection and decade for the Mainstream and Diversity collections. We also show the share of the U.S. population by race/ethnicity for each decade as a comparison. We classify famous people using methods described in Section IV.B. We collapse the following identities: East Asian, Middle Eastern, and South Asian into the Asian category; North American Indigenous peoples and South American Indigenous peoples into the Indigenous category; and African American and Black African into the Black category. If an individual was coded as having more than one race, we classify them as multiracial. Note that this is an analog to Figure VI, only with the y-axis collapsed to the maximum level for each race/ethnicity, respectively, to present easier-to-parse patterns for groups with lower levels of representation.

FIGURE BVI

Race Classification of Pictured Characters



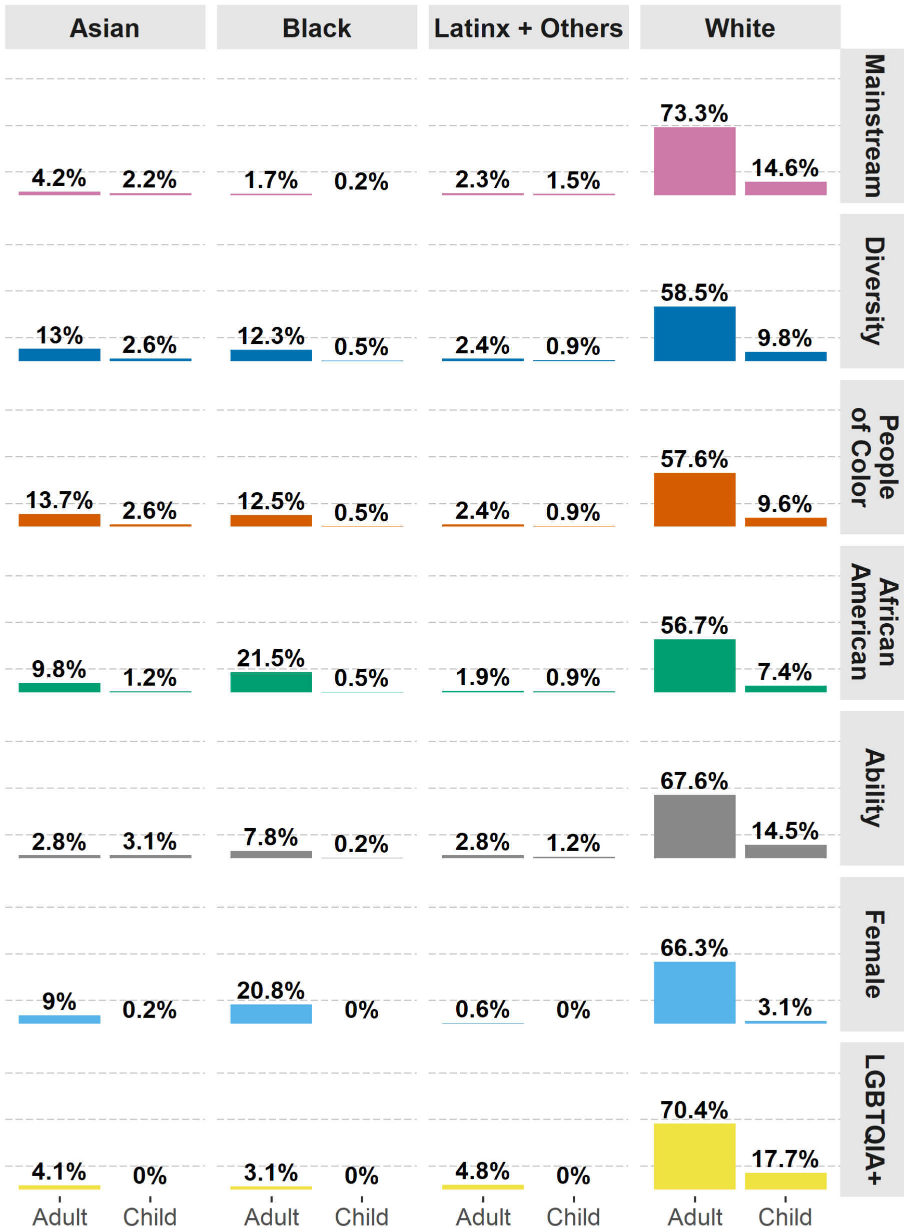

*Note:* In this figure, we show the proportion of faces in a book which our model labels as a given race averaged over all books in a collection. We first find the proportion of faces in each racial category for every book; then we average across all books in a collection. We detect faces using our face detection model (FDAI) described in Section IV.A.1. Within these faces, we classify race using an AutoML algorithm we trained using the UTKFace public data set.

FIGURE BVII

Share of U.S. Population and Pictured Characters, by Identity


*Note:* In this figure, we show the share of the U.S. population of specific identities mapped on the share of the pictured characters classified as a given identity in a given book averaged over all books in collection and decade. In Panel A, we show this by race/ethnicity. Each race/ethnicity category is constructed to be mutually exclusive. In Panel B, we show this by gender. In Panel C, we show this by age group.

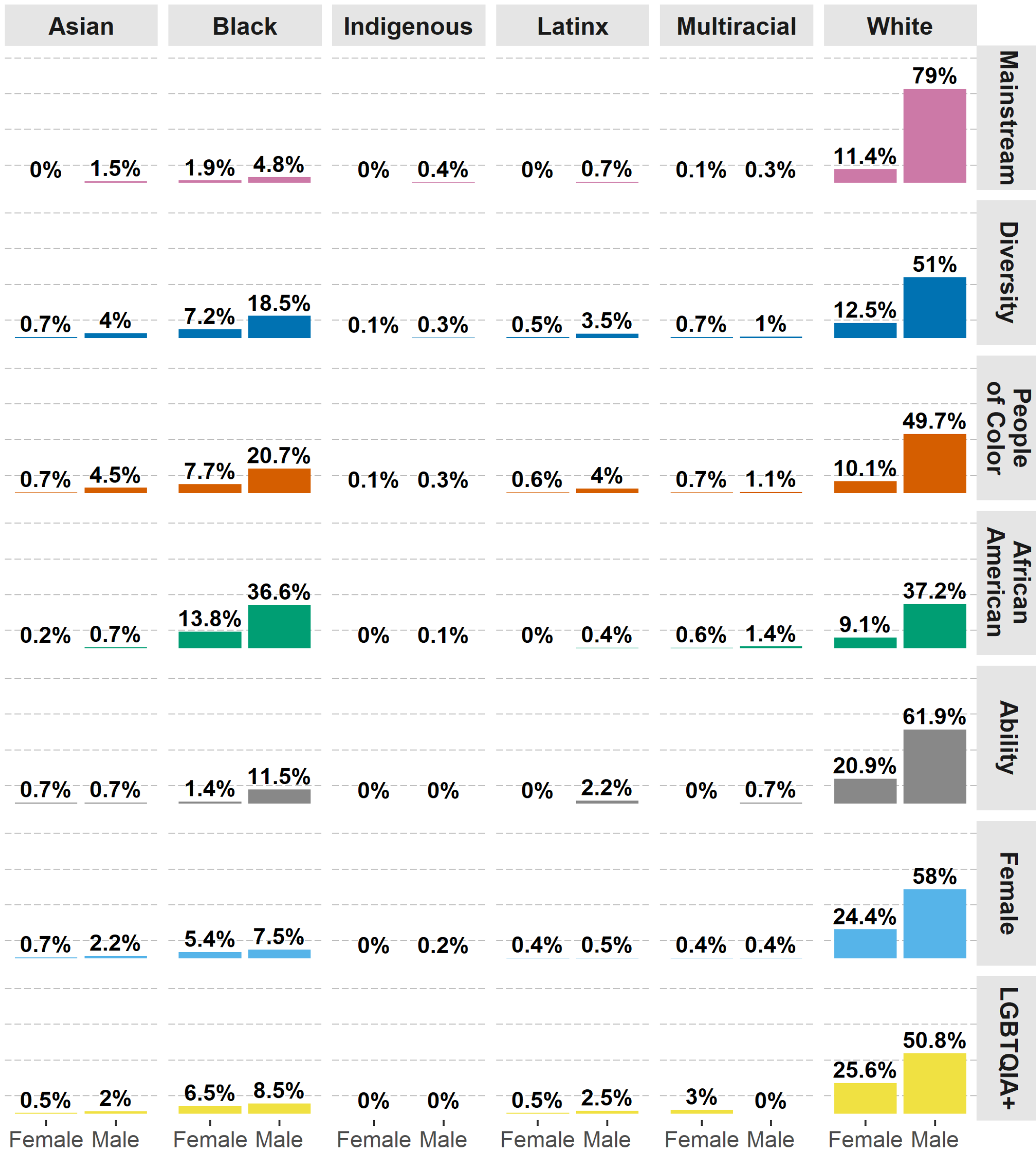
FIGURE BVIII
Race and Age Predictions of Pictured Characters




*Note:* In this figure, we show the proportion of detected faces in all collections by race and age predictions. We first find the proportion of faces in each race and age category for every book; then we average across all books in a collection. Race and age were classified by our trained AutoML model as described in Section IV.A.3. See Appendix Figure BVI for the same figure broken down by race alone.

FIGURE BIX

Race and Gender Classifications of Famous Figures in the Text

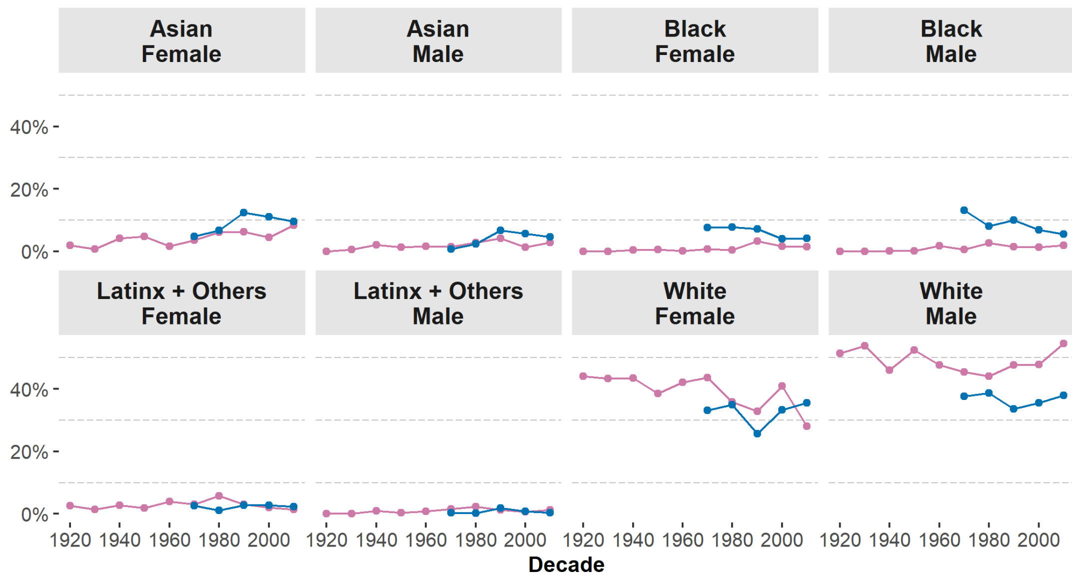



*Note:* In this figure, we count the number of famous people mentioned at least once in a given book and sum over all books in a collection. We then show the percentage breakdown of these famous people by race and gender. For example, if Aretha Franklin was mentioned at least once in two separate books within the Diversity collection, we would count her twice for that collection. We identify famous individuals and their predicted gender using methods described in Section IV.B. We manually label the race of famous individuals. We collapse the following identities: East Asian, Middle Eastern, and South Asian into the Asian category; North American Indigenous peoples and South American Indigenous peoples into the Indigenous category; and African American and Black African into the Black category. If an individual was coded as having more than one race, we classify them as multiracial. See Appendix Figure BIV for the same figure broken down by race alone.

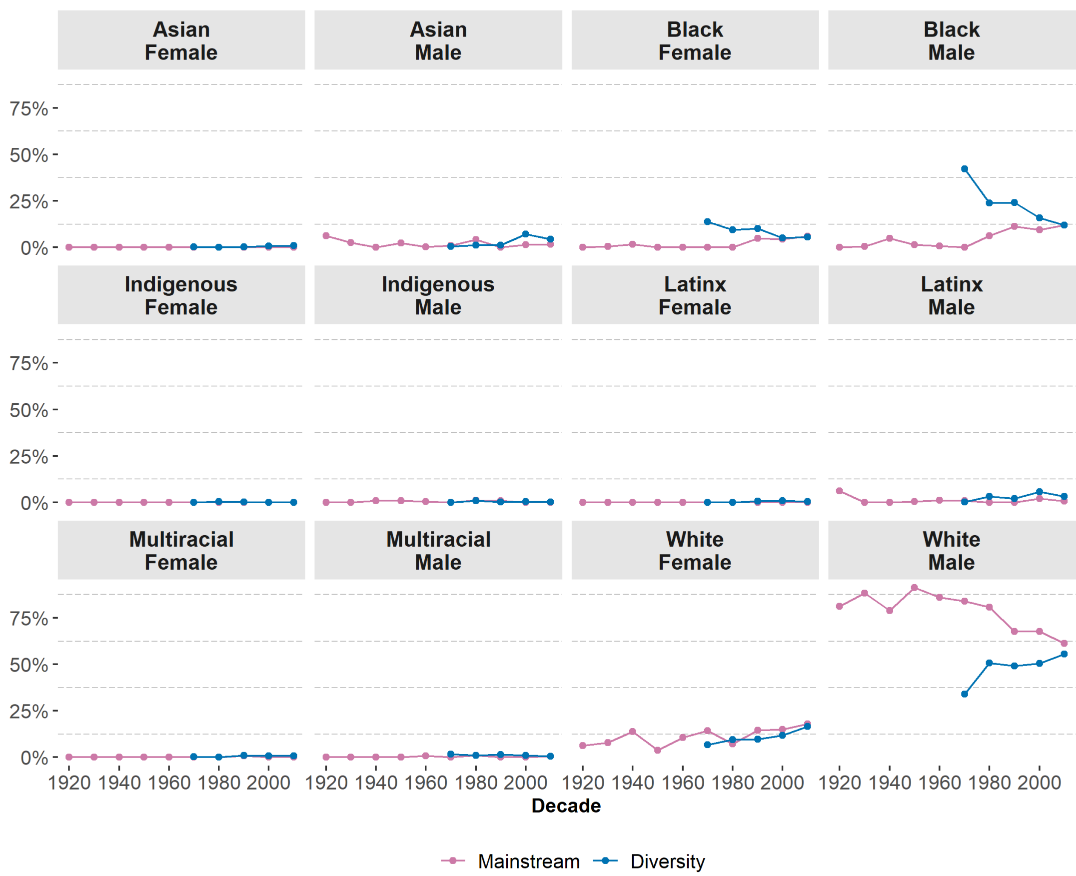
FIGURE BX

Proportion of Characters in Images and Text, by Race and Gender

(a) Detected Faces (Images)



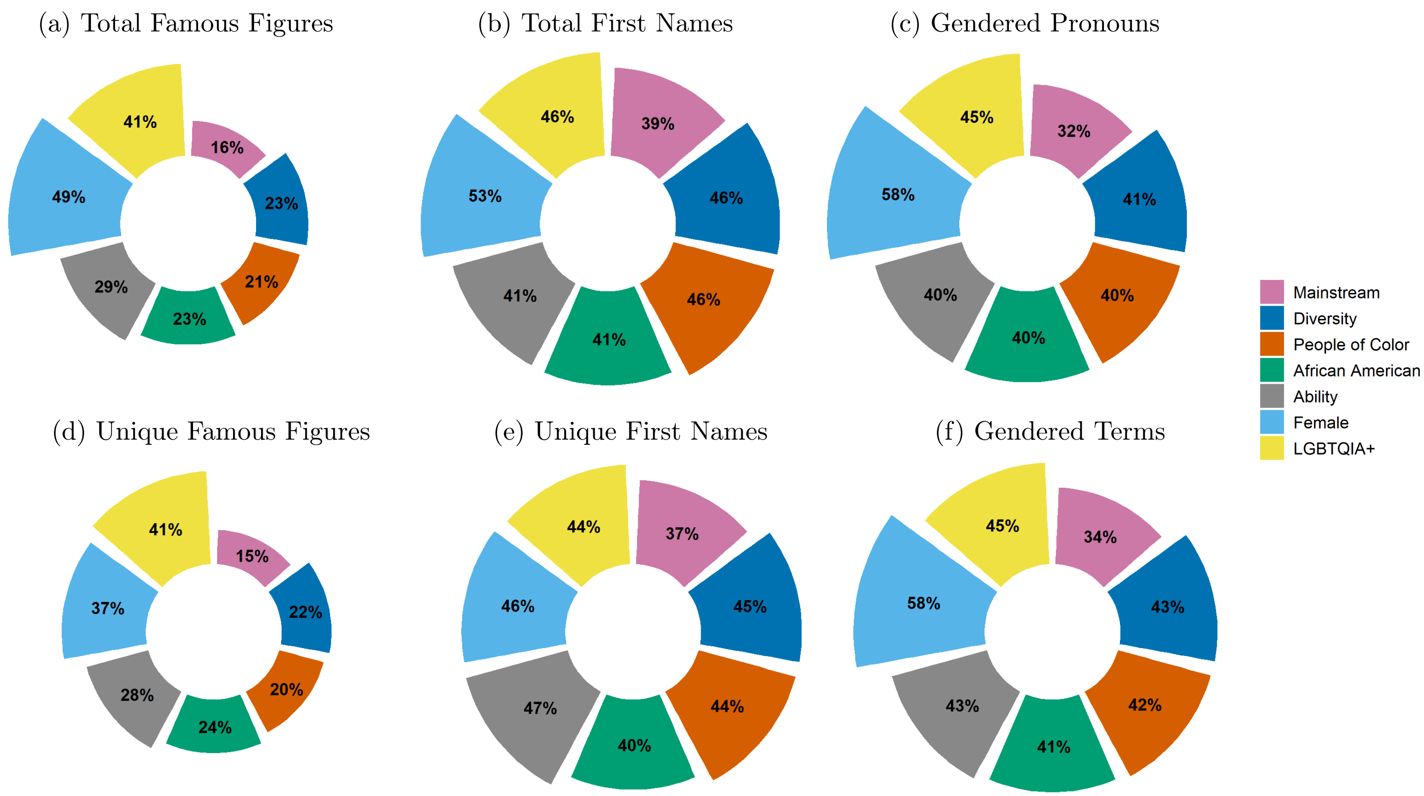

(b) Famous Figures (Text)




*Note:* In this figure, we show the share of the characters by race and gender in a given book averaged over all books in a collection and decade. In Panel A, we show this for detected faces in images. In Panel B, we show this for famous figures mentioned in the text.

FIGURE BXI

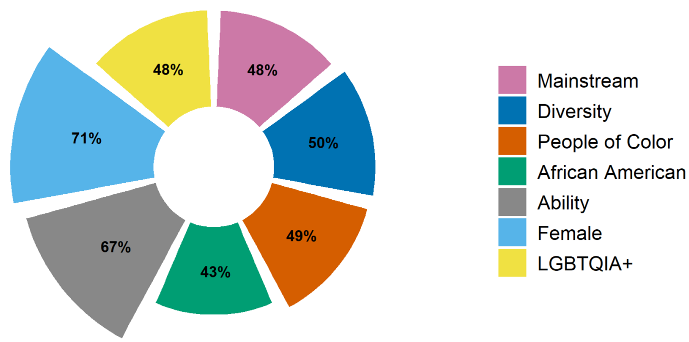
Female Representation in Text, by Type of Word



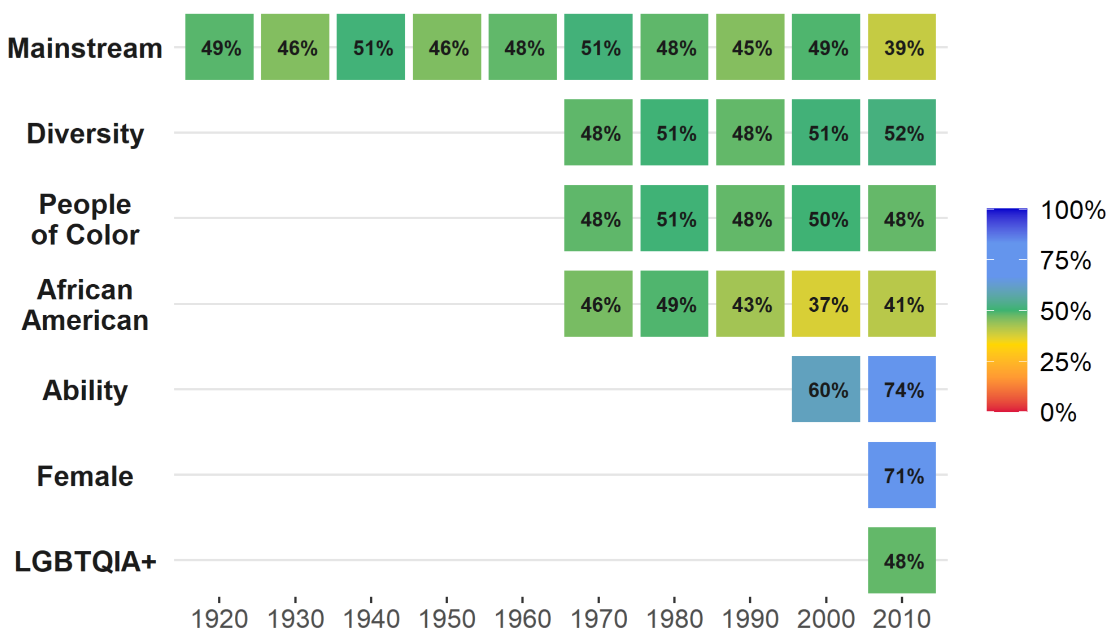

*Note:* In this figure, we show the proportion of female representation in the text by collection and type of word. In Panel A, we show the percent breakdown of female famous people mentioned in a given book, averaged over all books in a collection. For example, if Aretha Franklin was mentioned 3 times in a book and Jimmy Carter is mentioned 2 times (and if these were the only famous individuals mentioned), then 60 percent of the famous people mentioned in that book would be female. In Panel B, we show the same thing as Panel A, but for mentions of character first names. Panel C shows the percentage of gendered pronouns which are female in a given book, averaged over all books in a collection. In Panel D, we show the percentage breakdown of unique female famous people in a collection. For example, if Aretha Franklin was uniquely mentioned in 3 different books within a collection and Jimmy Carter is uniquely mentioned in 2 books within the same collection (and if these were the only famous individuals mentioned), then 60 percent of the unique famous people mentioned in that collection would be female. In Panel E, we show the same thing as Panel D but for unique character first names and Panel F shows the percentage of female terms (full list provided in Data Appendix).

FIGURE BXII
Proportion of Detected Faces Which Are Female-Presenting

(a) Percent of Female-Presenting Faces Detected, Overall

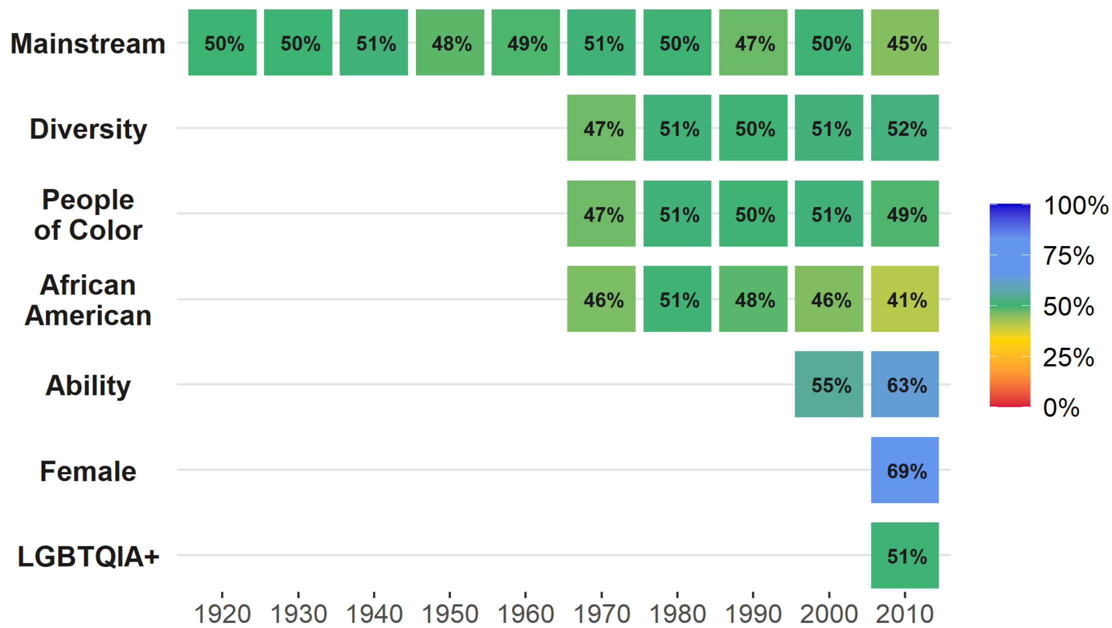



(b) Percent of Female-Presenting Faces Detected, Over Time



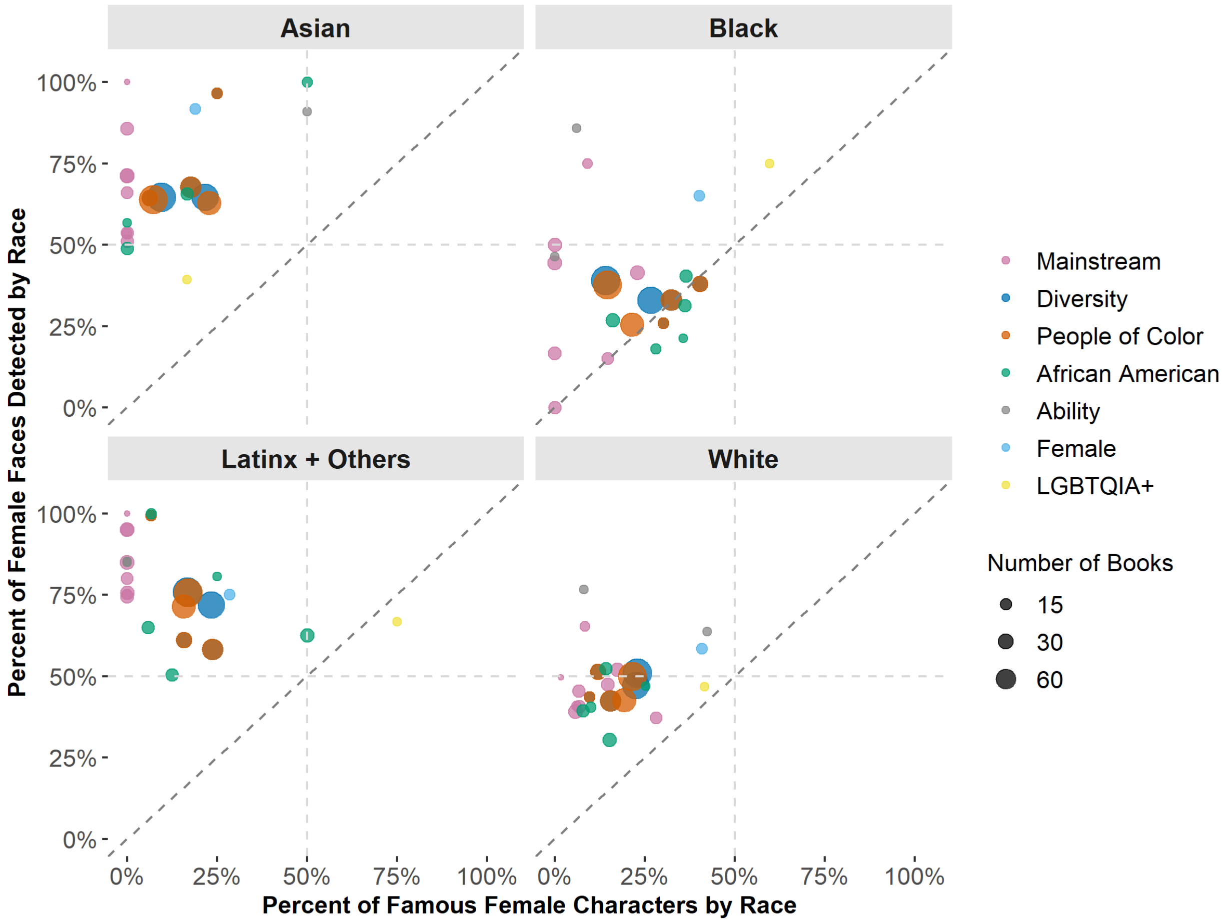

*Note:* In this figure, we show the proportion of faces in a book which our model labels as female. In Panel A, we show collection-level averages of the proportion of female faces in a given book by averaging over all books in a collection. In Panel B, we show these values over time by averaging the proportion of female faces in a given book by each collection and decade.

FIGURE BXIII
Average Probability a Face is Female, by Decade and Collection




*Note:* In this figure, we present the average probability that a face was classified as being female in a given collection by decade. We classify gender using an AutoML algorithm trained on the UTKFace public data set.

FIGURE BXIV
Race and Gender Representation in Images and Text

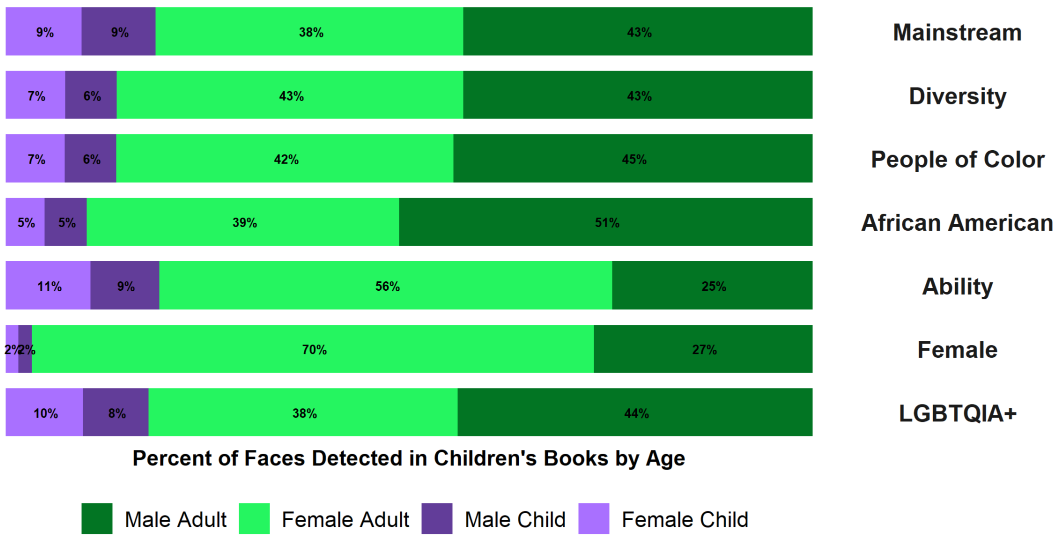



*Note:* In this figure, we plot female faces by race as a proportion of all faces with a given race classification on the y-axis and famous female characters by race as a proportion of all famous characters with a given race classification on the x-axis.

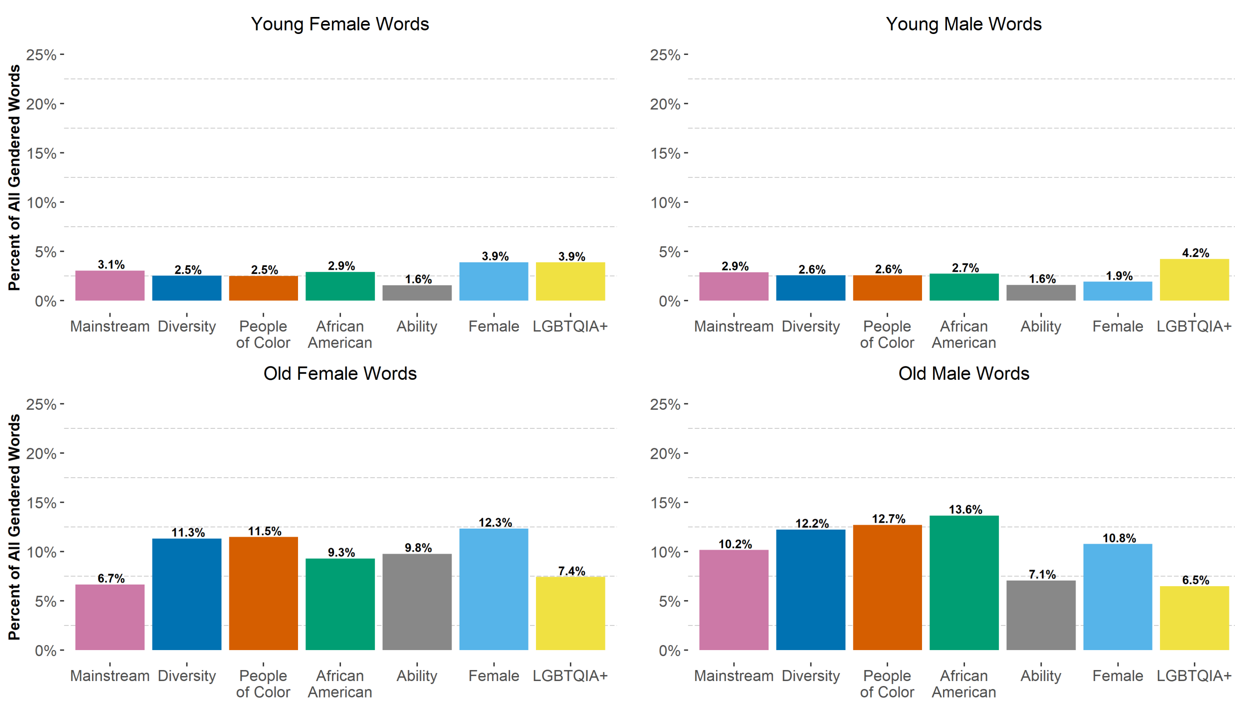
FIGURE BXV

Representation of Age in Images and Text

(a) Percent of Faces by Predicted Age Group and Gender



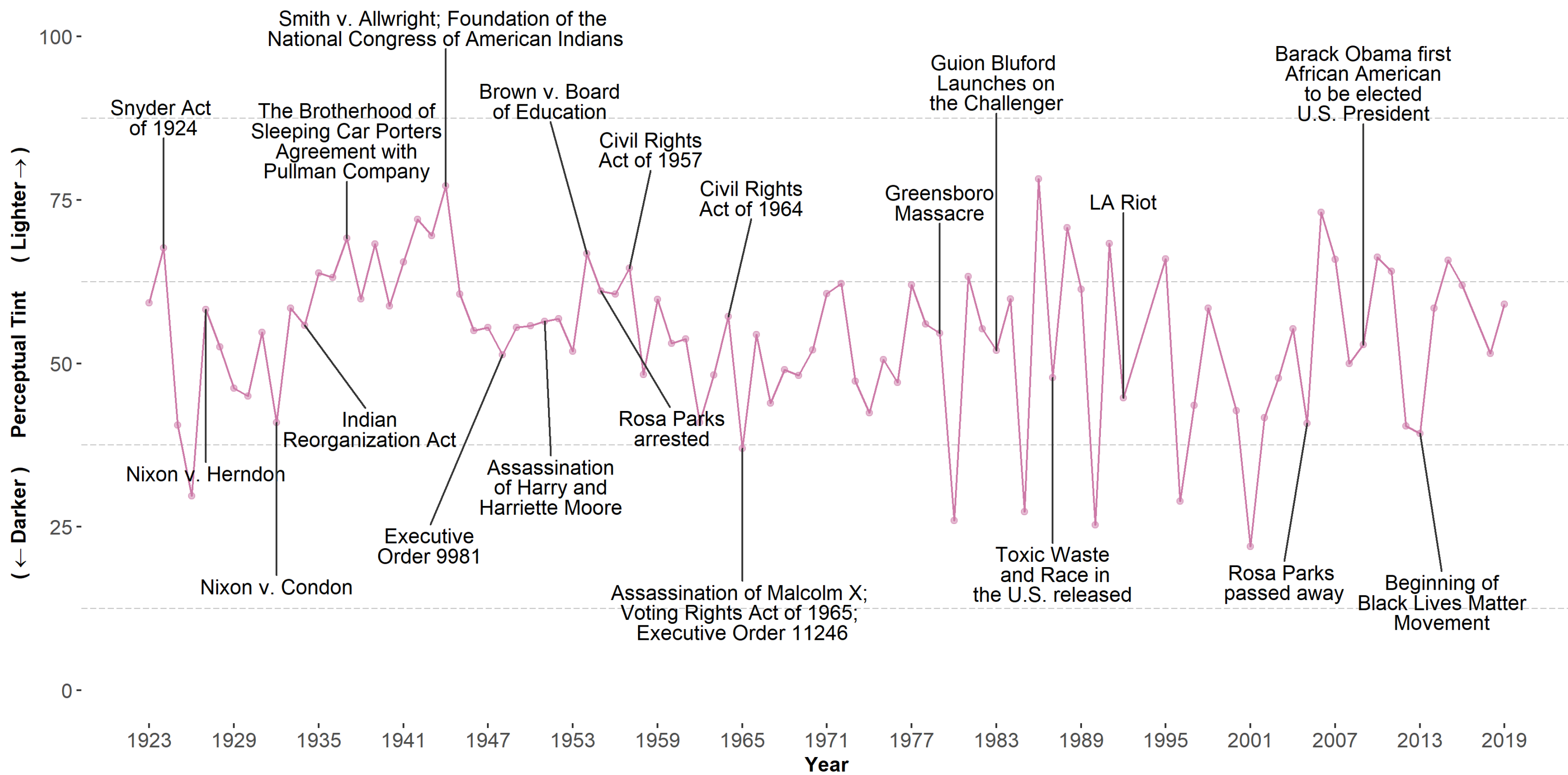

(b) Percent of Gendered Words by Age Group




*Note:* In this figure, we show analysis of the representation of age and gender. In Panel A, we show analysis of predicted age and gender in the faces in images. Specifically, we plot the proportion of identified faces classified in each age (adult vs. child) and gender (female vs. male) category. In Panel B, we show analysis of age and gender in text. Specifically, we plot the proportion of terms that refer to specific gender-age combinations (e.g., female adults such as queen or male children such as son) as a percent of all gendered terms in the book. We list the pre-specified gendered terms in the Data Appendix.

FIGURE BXVI

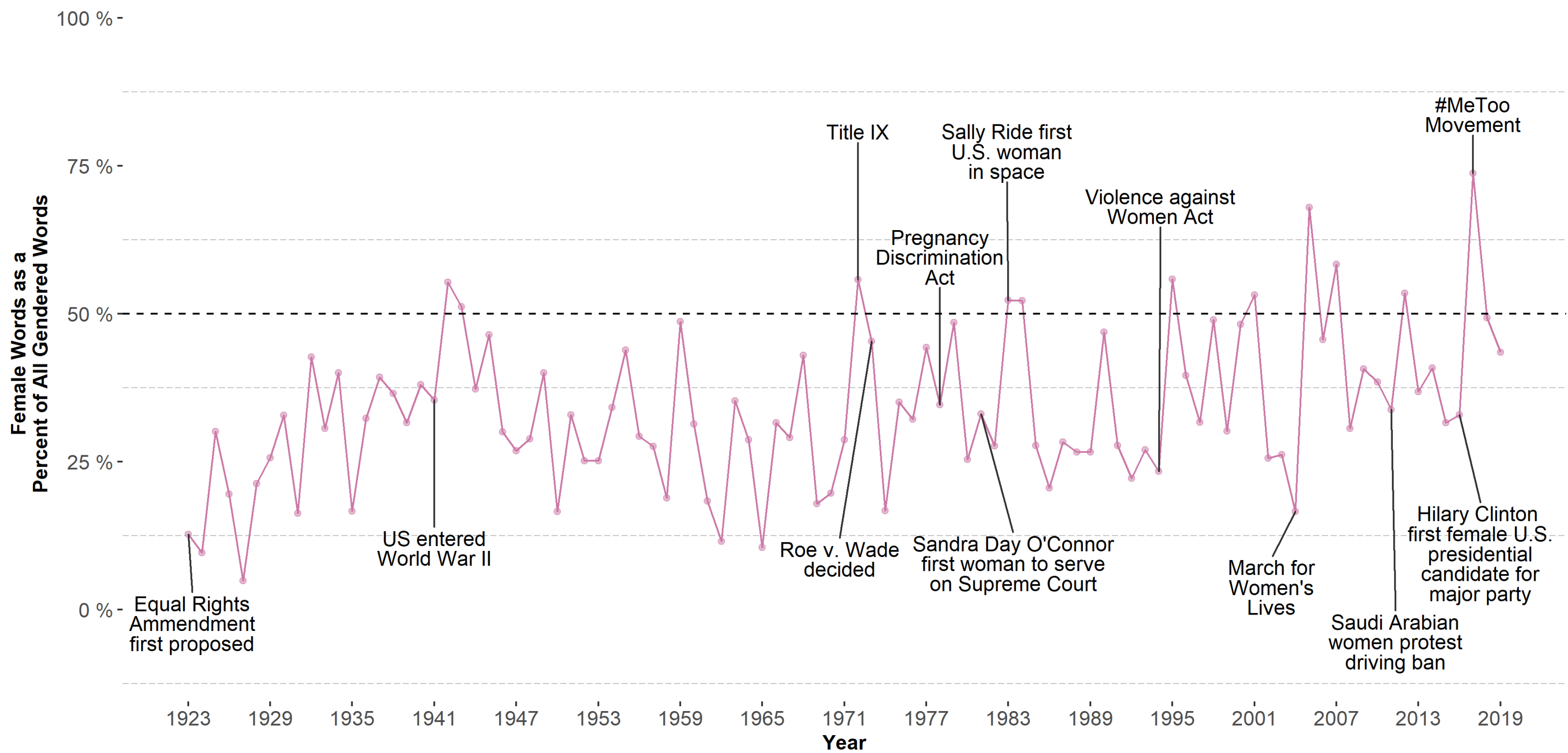
Mainstream Representation of Skin Color and Relevant Historical Events




*Note:* In this figure, we juxtapose measures of representation of skin color of pictured character faces from the Mainstream collection with the timing of salient historical events.

FIGURE BXVII

Mainstream Representation of Gender and Relevant Historical Events

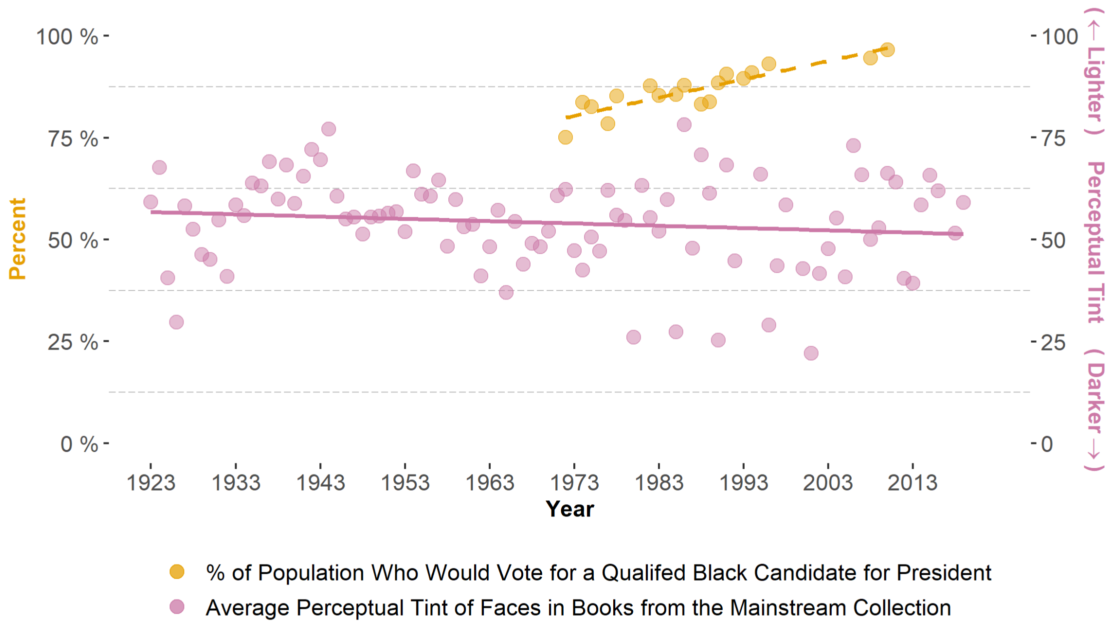



*Note:* In this figure, we juxtapose textual measures of gender representation from the Mainstream collection with the timing of salient historical events.

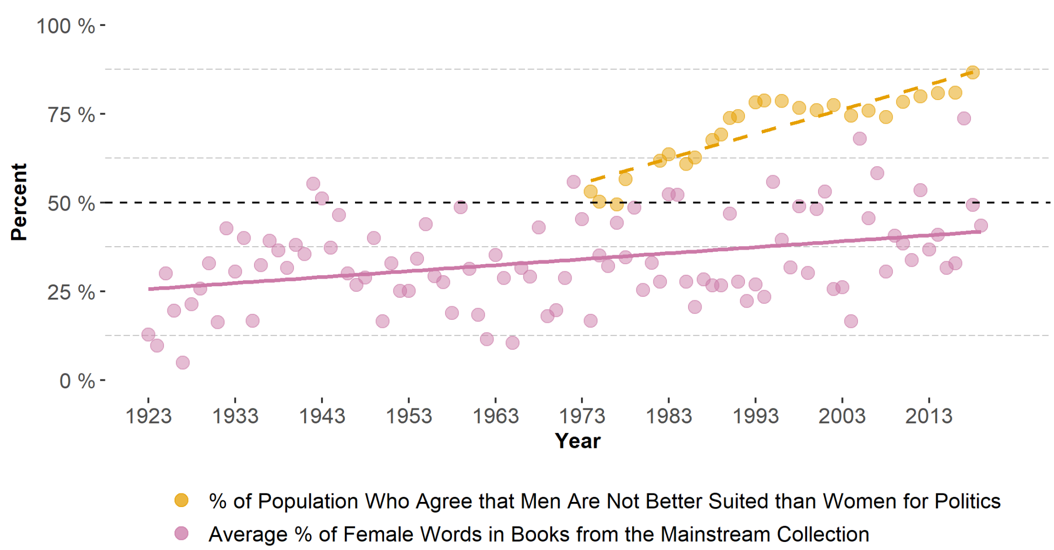
FIGURE BXVIII

Mainstream Representation and Social Attitudes Over Time

(a) Race



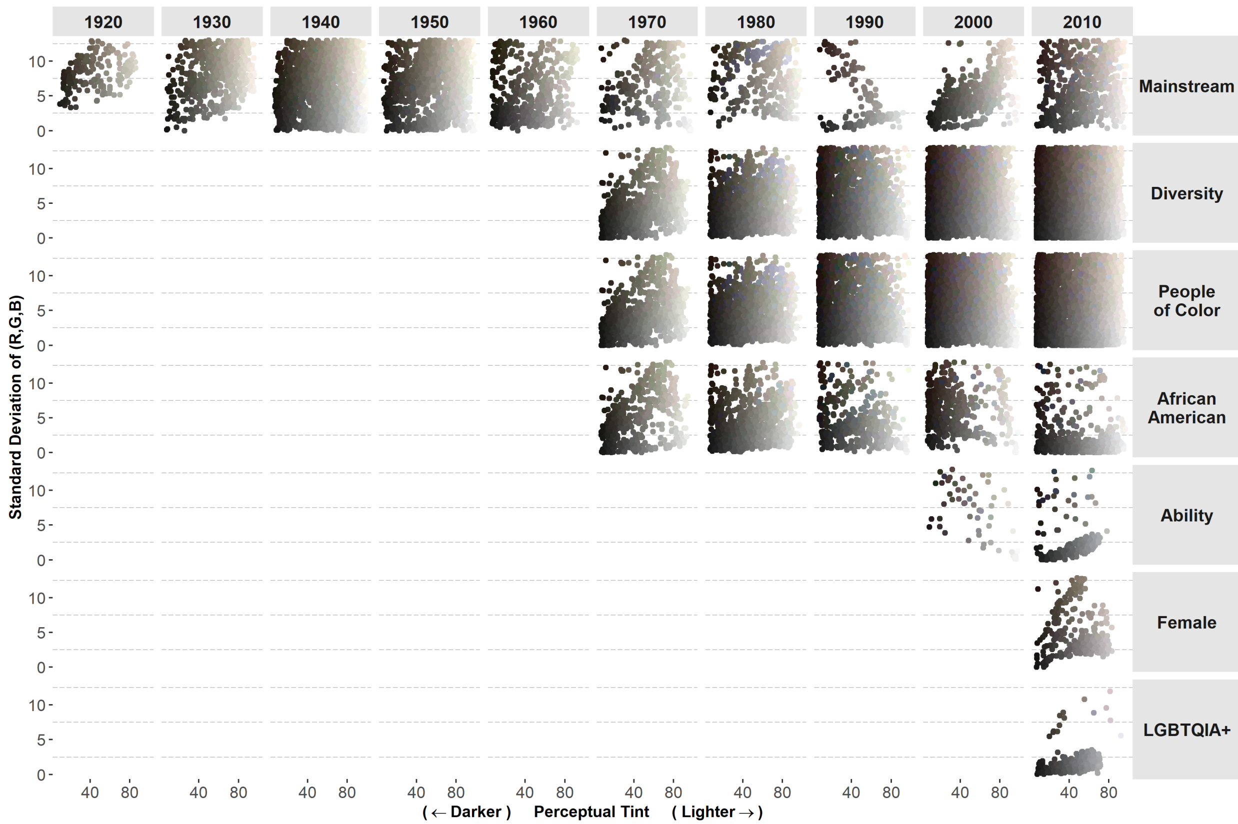

(b) Gender




*Note:* In this figure we compare trends in social attitudes with yearly representation in the Mainstream collection over time. In Panel A, we show the proportion of respondents who would vote for a qualified Black candidate for president along with the average skin tint of faces found in books within the Mainstream collection by year. In Panel B, we show the proportion of respondents who agree that men are not better suited than women for politics along with the average percent of female words in books within the Mainstream collection by year. Our data on social attitudes comes from the General Social Survey (GSS).

## C Non-Typical Skin Color Appendix

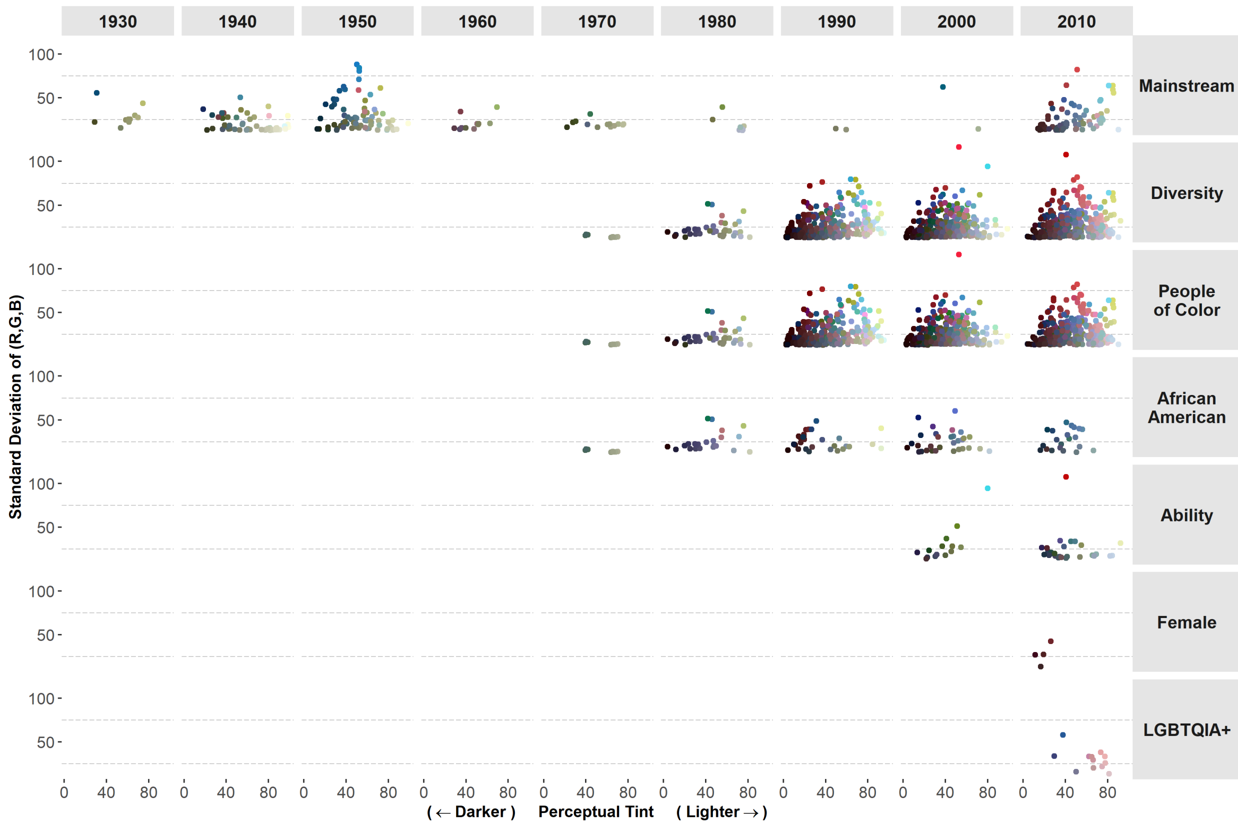
FIGURE CI
Skin Color Data Over Time, Monochromatic Skin Colors




*Note:* In this figure, we show an analog to Figure BII, here focusing on the representative skin colors for all detected faces with monochromatic skin colors (e.g., black and white) in each collection-by-decade cell. As described in Section IV.A, we use our face detection model (FDAI) trained on illustrations to classify faces in images. We determine a face's representative skin color using methods described in Section IV.A.2.

FIGURE CII

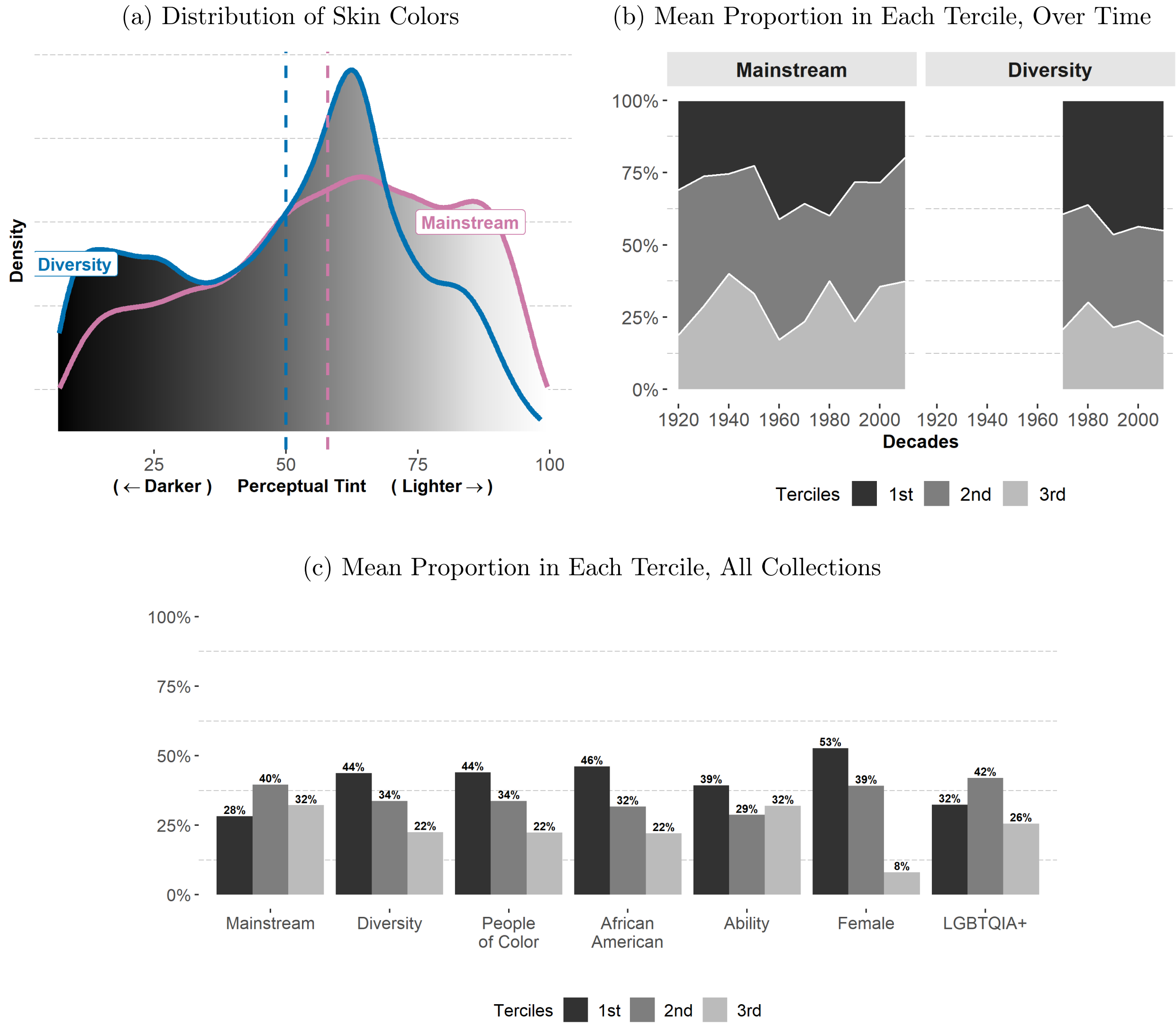
Skin Color Data Over Time, Polychromatic Non-Typical Skin Colors




*Note:* In this figure, we show an analog to Appendix Figure BII, here focusing on the representative skin colors for all detected faces with non-typical skin colors (e.g., blue or green) in each collection-by-decade cell. As described in Section IV.A, we use our face detection model (FDAI) trained on illustrations to classify faces in images. We determine a face's representative skin color using methods described in Section IV.A.2. The data shown in this figure begin in the 1930s, as opposed to in the 1920s as in Appendix Figures BII and CI, because we detect no faces with polychromatic non-typical skin colors in books from the 1920s.

FIGURE CIII

Skin Colors in Faces, by Collection: Monochromatic Skin Colors

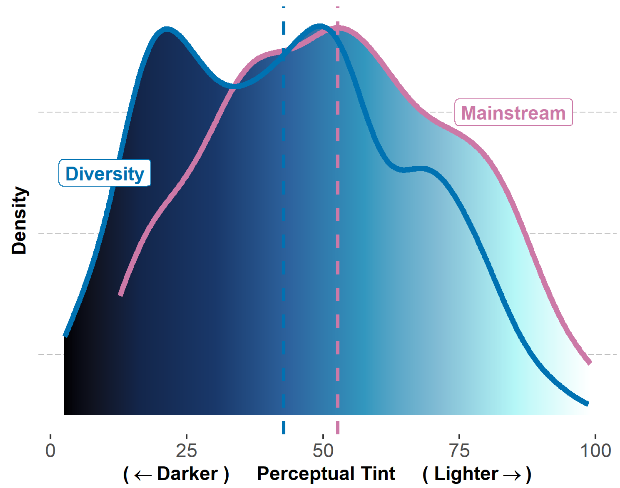



*Note:* This figure shows our analysis of the representative skin colors of the individual faces we detect in the images found in the books we analyze. This is an analog to Figure IV, only here we focus on monochromatic faces. Panel A shows the distribution of skin color tint for faces detected in books from the Mainstream and Diversity collections. The mean for each distribution is denoted with a dashed line. In Panel B, we show the average proportion of faces in each tercile, over time, for faces in the Mainstream and Diversity collections. Panel C shows the overall collection-specific average proportion of faces in each skin color tercile for each of the seven collections. Skin classification methods are described in Section IV.A.

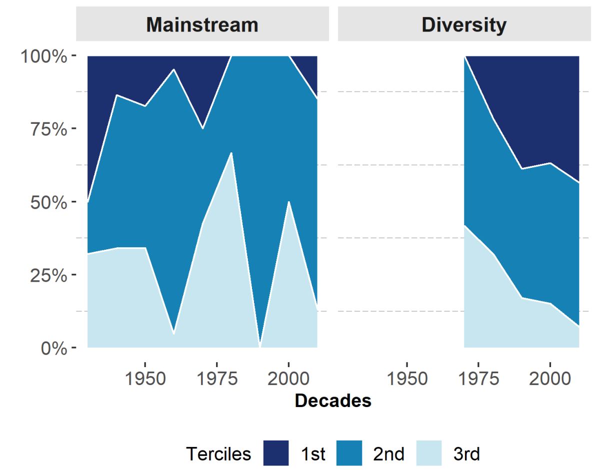
FIGURE CIV

Skin Colors in Faces, by Collection: Polychromatic Non-Typical Skin Colors

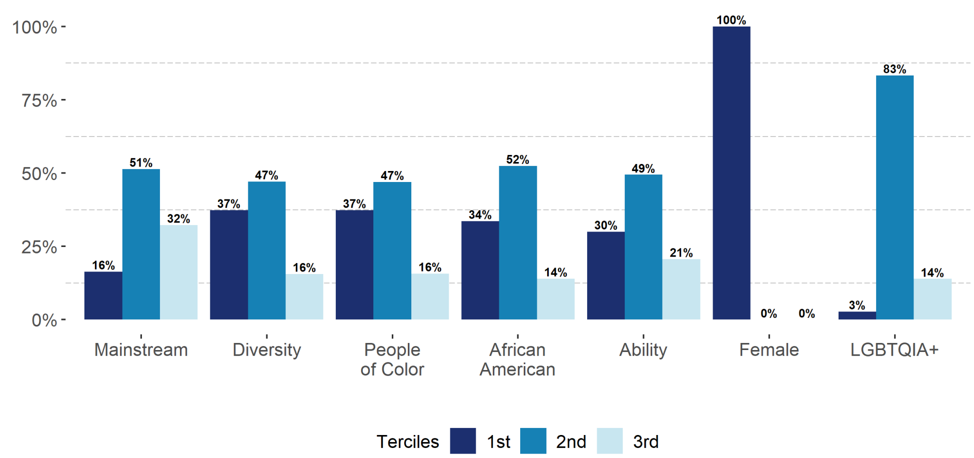
(a) Distribution of Skin Colors




(b) Mean Proportion in Each Tercile, Over Time



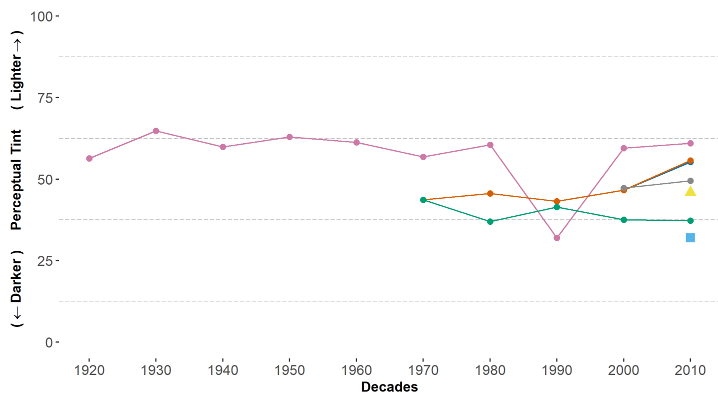

(c) Mean Proportion in Each Tercile, All Collections



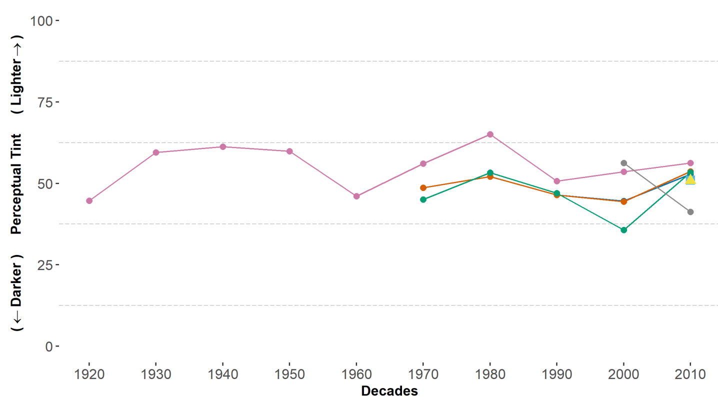

*Note:* This figure shows our analysis of the representative skin colors of the faces detected in the books we analyze. This is an analog to Figure IV, only here we focus on faces that have non-typical skin colors. Panel A shows the distribution of skin color tint for faces detected in books from the Mainstream and Diversity collections. The mean for each distribution is denoted with a dashed line. In Panels B and C, we show the average proportion of faces in each tercile of the perceptual tint distribution across all books in a collection. In Panel B, we show the average proportion of faces in each tercile, over time, for faces in the Mainstream and Diversity collections. Panel C shows the overall collection-specific average proportion of faces in each skin color tercile for each of the seven collections. Skin classification methods are described in Section IV.A.

FIGURE CV
Skin Colors over Time, by Collection

(a) Human Skin Colors




(b) Monochromatic Skin Colors

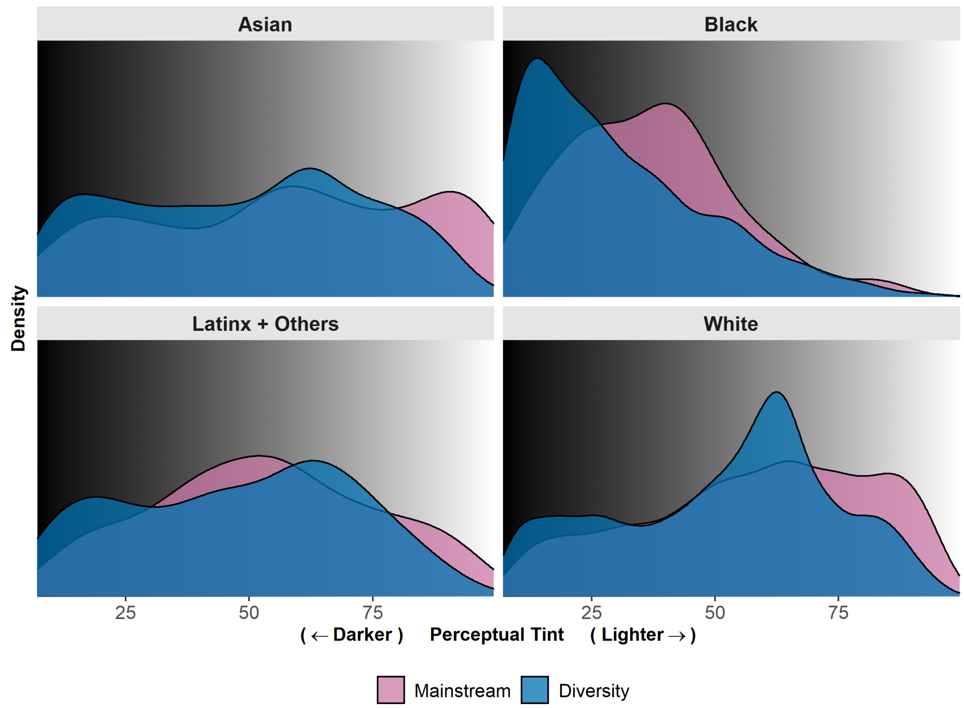



(c) Polychromatic Non-Typical Skin Colors

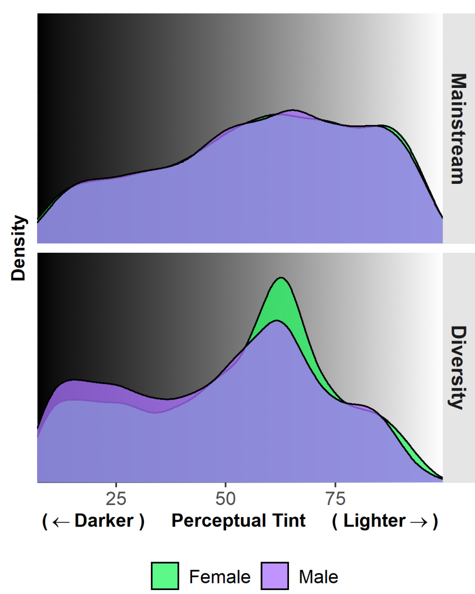

Note: This figure shows the average skin tint over time in our sample of award-winning children's books. We first take the average skin tint for all faces in a given book, then we average across all books in a given year. We separate the faces by skin color type, Panel A shows the average skin tint for all faces with human skin colors, Panels B and C show the same thing as Panel A but for Monochromatic and Polychromatic Non-typical Skin Colors, respectively.

FIGURE CVI
Skin Color by Predicted Race of Pictured Characters: Monochromatic Faces

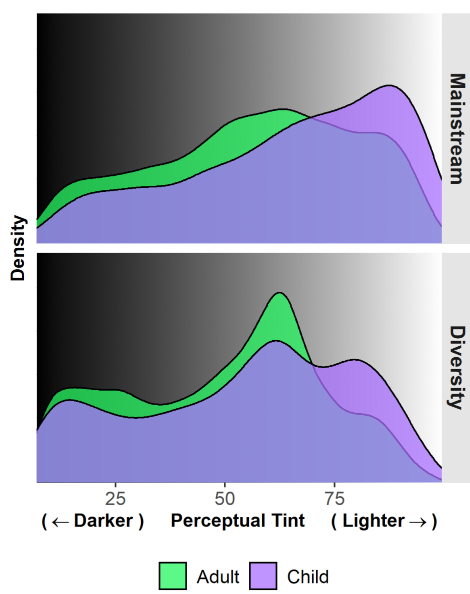
(a) Skin Color Distribution by Race




(b) Skin Color Distribution by Gender




(c) Skin Color Distribution by Age




*Note:* This figure shows the distribution of skin color tint by predicted race, gender, and age of the detected faces in the Mainstream and Diversity collections. This is an analog to Figure V, only here focusing on faces depicted in a monochromatic color scheme (e.g., black and white).

# D Award Criteria

We selected children's book awards featured on the ALSC website at the time of writing this paper, many of which are administered by different organizations. In this section we give the criteria for award selection for the Newbery and Caldecott awards and provides links to the criteria for the other awards.

## D.A Caldecott Medal Criteria

Terms and criteria are listed below.[1] Note that the numbering and itemization follows the formatting as presented on the website and were not altered for consistency.

### D.A.1 Terms

The Medal shall be awarded annually to the artist of the most distinguished American picture book for children published by an American publisher in the United States in English during the preceding year. There are no limitations as to the character of the picture book except that the illustrations be original work. Honor books may be named. These shall be books that are also truly distinguished.

The award is restricted to artists who are citizens or residents of the United States. Books published in a U.S. territory or U.S. commonwealth are eligible.

The committee in its deliberations is to consider only books eligible for the award, as specified in the terms.

### D.A.2 Definitions

A "picture book for children" as distinguished from other books with illustrations, is one that essentially provides the child with a visual experience. A picture book has a collective unity of story-line, theme, or concept, developed through the series of pictures of which the book is comprised.

A "picture book for children" is one for which children are an intended potential audience. The book displays respect for children's understandings, abilities, and appreciations. Children are defined as persons of ages up to and including fourteen and picture books for this entire age range are to be considered.

"Distinguished" is defined as:

- Marked by eminence and distinction; noted for significant achievement.
- Marked by excellence in quality.
- Marked by conspicuous excellence or eminence.
- Individually distinct.
- The artist is the illustrator or co-illustrators. The artist may be awarded the medal posthumously.

[1] Terms and criteria downloaded exactly from https://www.ala.org/alsc/awardsgrants/bookmedia/caldecott on July 14, 2022.

The term "original work" may have several meanings. For purposes of these awards, it is defined as follows: "Original work" means that the illustrations were created by this artist and no one else. Further, "original work" means that the illustrations are presented here for the first time and have not been previously published elsewhere in this or any other form. Illustrations reprinted or compiled from other sources are not eligible.

“American picture book in the United States” means that books first published in previous years in other countries are not eligible. Books published simultaneously in the U.S. and another country may be eligible. Books published in a U.S. territory or U.S. commonwealth are eligible.

“In English” means that the committee considers only books written and published in English. This requirement DOES NOT limit the use of words or phrases in another language where appropriate in context.

“Published…in the preceding year” means that the book has a publication date in that year, was available for purchase in that year, and has a copyright date no later than that year. A book might have a copyright date prior to the year under consideration but, for various reasons, was not published until the year under consideration. If a book is published prior to its year of copyright as stated in the book, it shall be considered in its year of copyright as stated in the book. The intent of the definition is that every book be eligible for consideration, but that no book be considered in more than one year.

“Resident” specifies that author has established and maintains a residence in the United States, U.S. territory, or U.S. commonwealth as distinct from being a casual or occasional visitor.

The term, “only the books eligible for the award,” specifies that the committee is not to consider the entire body of the work by an artist or whether the artist was previously recognized by the award. The committee’s decision is to be made following deliberation about books of the specified calendar year.

### D.A.3 Criteria

In identifying a “distinguished American picture book for children,” defined as illustration, committee members need to consider:

- Excellence of execution in the artistic technique employed;
- Excellence of pictorial interpretation of story, theme, or concept;
- Appropriateness of style of illustration to the story, theme or concept;
- Delineation of plot, theme, characters, setting, mood or information through the pictures;
- Excellence of presentation in recognition of a child audience.

The only limitation to graphic form is that the form must be one which may be used in a picture book. The book must be a self-contained entity, not dependent on other media (i.e., sound, film or computer program) for its enjoyment.

Each book is to be considered as a picture book. The committee is to make its decision primarily on the illustration, but other components of a book are to be considered especially when they make a book less effective as a children's picture book. Such other components might include the written text, the overall design of the book, etc.

Note: The committee should keep in mind that the award is for distinguished illustrations in a picture book and for excellence of pictorial presentation for children. The award is not for didactic intent or for popularity.

Adopted by the ALSC board, January 1978. Revised, Midwinter 1987. Revised, Annual 2008.

## D.B Newbery Medal Criteria

Terms and criteria are listed below.[2] Note that the numbering and itemization follows the formatting as presented on the website and were not altered for consistency.

### D.B.1 Terms

1. The Medal shall be awarded annually to the author of the most distinguished contribution to American literature for children published by an American publisher in the United States in English during the preceding year. There are no limitations as to the character of the book considered except that it be original work. Honor books may be named. These shall be books that are also truly distinguished.

2. The Award is restricted to authors who are citizens or residents of the United States.

3. The committee in its deliberations is to consider only the books eligible for the award, as specified in the terms.

### D.B.2 Definitions

1. "Contribution to American literature" indicates the text of a book. It also implies that the committee shall consider all forms of writing—fiction, non-fiction, and poetry. Reprints, compilations and abridgements are not eligible.

2. A "contribution to American literature for children" shall be a book for which children are an intended potential audience. The book displays respect for children's understandings, abilities, and appreciations. Children are defined as persons of ages up to and including fourteen, and books for this entire age range are to be considered.

3. "Distinguished" is defined as:

    - Marked by eminence and distinction; noted for significant achievement.
    - Marked by excellence in quality.
    - Marked by conspicuous excellence or eminence.
    - Individually distinct.

[2] Terms and criteria downloaded exactly from https://www.ala.org/alsc/awardsgrants/bookmedia/newbery on July 14, 2022.

4. “Author” may include co-authors. The author(s) may be awarded the medal posthumously.
5. The term "original work" may have several meanings. For purposes of these awards, it is defined as follows:
   - "Original work" means that the text was created by this writer and no one else. It may include original retellings of traditional literature, provided the words are the author’s own.
   - Further, "original work" means that the text is presented here for the first time and has not been previously published elsewhere in this or any other form. Text reprinted or compiled from other sources are not eligible. Abridgements are not eligible.
6. “In English” means that the committee considers only books written and published in English. This requirement DOES NOT limit the use of words or phrases in another language where appropriate in context.
7. “American literature published in the United States” means that books first published in previous years in other countries are not eligible. Books published simultaneously in the U.S. and another country may be eligible. Books published in a U.S. territory, or U.S. commonwealth are eligible.
8. “Published… in the preceding year” means that the book has a publication date in that year, was available for purchase in that year, and has a copyright date no later than that year. A book might have a copyright date prior to the year under consideration but, for various reasons, was not published until the year under consideration. If a book is published prior to its year of copyright as stated in the book, it shall be considered in its year of copyright as stated in the book. The intent of the definition is that every book be eligible for consideration, but that no book be considered in more than one year.
9. “Resident” specifies that the author has established and maintains a residence in the United States, U.S. territory, or U.S. commonwealth as distinct from being a casual or occasional visitor.
10. The term, “only the books eligible for the award,” specifies that the committee is not to consider the entire body of the work by an author or whether the author was previously recognized by the award. The committee’s decision is to be made following deliberation about the books of the specified calendar year.

### D.B.3 Criteria

1. In identifying “distinguished contribution to American literature,” defined as text, in a book for children,
   (a) Committee members need to consider the following:
      - Interpretation of the theme or concept

- Presentation of information including accuracy, clarity, and organization
- Development of a plot
- Delineation of characters
- Delineation of a setting
- Appropriateness of style.

Note: Because the literary qualities to be considered will vary depending on content, the committee need not expect to find excellence in each of the named elements. The book should, however, have distinguished qualities in all of the elements pertinent to it.

(b) Committee members must consider excellence of presentation for a child audience.

2. Each book is to be considered as a contribution to American literature. The committee is to make its decision primarily on the text. Other components of a book, such as illustrations, overall design of the book, etc., may be considered when they make the book less effective.
3. The book must be a self-contained entity, not dependent on other media (i.e., sound or film equipment) for its enjoyment.

Note: The committee should keep in mind that the award is for literary quality and quality presentation for children. The award is not for didactic content or popularity.

Adopted by the ALSC Board, January 1978. Revised, Midwinter 1987. Revised, Annual 2008.

### D.C Award Information for Diversity Collection

In this section, we provide the website describing each award and its selection criteria, accessed on July 15, 2022. Selection criteria vary by award. At a high level, they share two main goals. One is to recognize excellence in the content of the book. This goal, and the text of the various award criteria given in the links below, tracks closely with the main goals of the Caldecott and Newbery awards. The second goal is to recognize books who portray, recognize, or elevate a specific identity group, for example, people with disabilities or Hispanic Americans. These goals vary widely by award, as each award focuses on a specific identity.

- American Indian Youth Literature Award
  Site: ailanet.org/activities/american-indian-youth-literature-award
- Américas Award
  Site: claspprograms.org/pages/detail/65/About-the-Award
- Name: Arab American Book Award
  Site: arabamericanmuseum.org/book-awards/
- Asian/Pacific American Award for Literature
  Site: apalaweb.org/awards/literature-awards/literature-award-guidelines/

- Carter G. Woodson Book Awards
  Site: woodsonawards.weebly.com/
- Coretta Scott King Book Award
  Site: ala.org/rt/emiert/cskbookawards/slction
- Dolly Gray Children's Literature Award
  Site: dollygrayaward.com/
- Ezra Jack Keats Award
  Site: degrummond.org/ezra-jack-keats-book-award-guidelin
- Middle East Book Award
  Site: meoc.us/book-awards.html
- Notable Books for a Global Society
  Site: clrsig.org/nbgs.html
- Pura Belpré Award
  Site: ala.org/alsc/awardsgrants/bookmedia/belpre
- Rise: A Feminist Book Project
  Site: risefeministbooks.wordpress.com/criteria/
- Schneider Family Book Award
  Site: ala.org/awardsgrants/awards/1/apply
- Skipping Stones Youth Honor Awards
  Site: skippingstones.org/wp/youth-honors-award/
- South Asia Book Award
  Site: southasiabookaward.wisc.edu/submission-guidelines/
- Stonewall Book Awards
  Site: ala.org/awardsgrants/awards/177/apply
- Tomás Rivera Mexican American Awards
  Site: education.txstate.edu/ci/riverabookaward/about.html

## E Data Appendix

In this section, we describe various pieces of the data we use in cases where we do not describe it in the body of the paper.

### E.A Google Trends data

We collect Google Trends data as a measure of general interest in the children's literature awards found within our sample. Note that Google Trends draws from a random sample of internet searches which have been filtered to remove duplicate search requests, uncommon searches, and searches with special characters. We only collect data on Google searches conducted between 12/04/2016 and 12/12/2021. We limit our analysis to awards that have topic IDs in the Google Trends data. Awards with topic IDs include the Amelia Bloomer Project (renamed Rise Feminist), Caldecott Medal, Coretta Scott King Award, Ezra Jack Keats Book Award, John Newbery Medal, Pura Belpré Award, Schneider Family Book Award, and Stonewall Book Award. Using these topic IDs, we measure weekly search interest across the U.S. for each children's book award.

### E.B Seattle Public Library Checkouts Data

To study the impact of being recognized by the children's book awards we examine, we analyze data from the Seattle Public Library system on all checkouts from the library between April 2005 and September 2017.[3] Awards are given near the end of January each year to books published in that year or the year before. We analyze checkout data for the universe of books that won an award in our sample (not just the books we digitized), alongside all books belonging to the children's and junior book collections published in the year prior to the award, covering award years 2005 to 2017.

We collapse these to a data set measuring the number of collection-by-day checkouts, scaled by the number of books in the collection to generate a measure of the average number of checkouts per book, per day, in each of the three collections. We limit checkout data for each book to approximately one calendar year before the award was given and the two following calendar years.

To generate Figure I, we re-center the checkout date according to its distance from the date in which the award is given for books published in that year. For example, books published in 2011 would be eligible for an award in 2012. Checkouts from before January 20th, 2012 (The first date of the ALA Midwinter Meeting in 2012) would be given negative values – for example, checkouts on January 10th, 2012, would be −10 days from January 20th, 2012. Checkouts after that date have positive values. Figure I shows the results of applying a 14-day moving average to each series of average collection-specific number of checkouts per day (divided by the number of books in that collection to account for the fact that the number of books per collection varies across the Mainstream, Diversity, and all other children's books) over the window of days to award spanning [–400 days, 730 days].

[3]These data are publicly available at https://data.seattle.gov/Community/Checkouts-by-Title/tmmm-ytt6; site accessed on April 15, 2021.

## F Library Checkout Event Study Appendix

We quantify the post-award increase using a simple event study design. While not causal per se, this allows us to estimate more precisely how much more likely books in each collection are to be checked out after being recognized by an award in our sample, relative to other children's books. To do so, we use the following equation:

$$checkouts_{cd} = \beta_1 Post + \beta_2 Post * Mainstream + \beta_3 Post * Diversity + \eta_c + \varepsilon_{cd}$$

The dependent variable is the average number of checkouts, per book, in collection $c$ on day $d$. We regress this on the following variables: whether the day is after January 20th ($Post$) (a noisy estimate of the date when the awards are announced each year); a set of fixed effects for each collection, $\eta_c$; and an interaction of the $Post$ variable with the $Mainstream$ and $Diversity$ collection variables.

TABLE FI
Estimates of the Increase in Daily Checkouts After Receipt of Mainstream and Diversity Awards

| | *Dependent variable:* |
|---|---|
| Parameter | Estimate |
| Non-Recognized Children's Books in Library Fixed Effect | 0.091*** |
| | (0.008) |
| Diversity Collection Fixed Effect | 0.063*** |
| | (0.005) |
| Mainstream Collection Fixed Effect | 0.173*** |
| | (0.005) |
| Post | 0.031*** |
| | (0.009) |
| Post x Diversity | 0.008 |
| | (0.011) |
| Post x Mainstream | 0.351*** |
| | (0.011) |
| Observations | 5,590 |
| Adjusted $R^2$ | 0.635 |

Notes: These parameters were generated using the equation given in this subsection and were estimated using data from the Seattle Public Library on daily checkouts. *p<0.1; **p<0.05; ***p<0.01

We present our results in Table FI. This shows that after being recognized by an award, Mainstream books are approximately four times as likely as non-recognized children's books in the library to be checked out on any given day. We derive this from calculating the ratio of the post-award checkout rate for the Mainstream collection to that of the non-recognized books. For the Mainstream collection, this is the sum of the *Mainstream* fixed effect, the coefficient on the "post-award" variable (*Post*), and the coefficient on the interaction term between *Post* and the *Mainstream* collection, which sums to approximately 0.474. The post-award checkout rate for non-recognized children's books in the library is the sum of the non-recognized children's books in the library fixed effect and the coefficient on *Post*, which sums to approximately 0.121.

An alternate interpretation is that after winning the award, the Mainstream collection books are approximately 2.9 times more likely to be checked out than they were before. This is derived by dividing the sum of coefficients on *Post*, the interaction of *Mainstream* and *Post*, and the *Mainstream* fixed effect, by the *Mainstream* fixed effect. We note that these should be interpreted as suggestive estimates; we define "pre-" and "post-" award using January 20th, an estimate of when news of the award announcements is likely to reach readers, parents, and librarians. Its precise date varies from year to year.

For the Diversity awards, we see a slight change in checkout behavior after January 20th. This can be seen in our estimate of the interaction term between *Diversity* and *Post*, which is statistically significant, but small in magnitude - especially when compared to the coefficient on the interaction term between *Mainstream* and *Post*. Seen through the lens of the calculations above, after receiving an award, Diversity collection books are more than 11 percent *less* likely to be checked out than non-winners; this can be derived analogously, comparing the post-award checkout rate for the Diversity collection – the sum of the *Diversity* fixed effect, the coefficient on *Post*, and the coefficient on the interaction term between *Post* and the *Diversity* collection, which sums to approximately 0.108. The post-award checkout rate for non-winners is the sum of the *Non-winners* fixed effect and the coefficient on *Post*, which is approximately 0.121. Prior to receipt of the award, they were approximately 28 percent less likely to be checked out.

In Table FII, we present an alternative specification where we estimate a similar equation, only with separate parameters for award winners and honorees. This shows broadly similar results, with one exception: winning a mainstream award yields a premium that is 2.5 times as large as merely being an honoree. This is similar to the visual patterns we see in Figure I and, more specifically, the distinct post-award increases in checkouts we observe for winners and awardees, respectively.

TABLE FII

Estimates of the Increase in Daily Checkouts After Receipt of Mainstream and Diversity Awards, Disaggregated by Winners and Honorees

| | *Dependent variable:* |
|---|---|
| Parameter | Estimate |
| Non-Recognized Children's Books in Library Fixed Effect | 0.091*** |
| | (0.006) |
| Mainstream Winner Fixed Effect | 0.185*** |
| | (0.006) |
| Mainstream Honoree Fixed Effect | 0.161*** |
| | (0.006) |
| Diversity Winner Fixed Effect | 0.066*** |
| | (0.006) |
| Diversity Honoree Fixed Effect | 0.059*** |
| | (0.006) |
| Post | 0.031*** |
| | (0.008) |
| Post x Mainstream Winner | 0.500*** |
| | (0.011) |
| Post x Mainstream Honoree | 0.201*** |
| | (0.011) |
| Post x Diversity Winner | 0.016 |
| | (0.011) |
| Post x Diversity Honoree | −0.001 |
| | (0.011) |
| Observations | 5,590 |
| Adjusted $R^2$ | 0.747 |

Notes: This table is similar to Table FI, except that it separates books by whether they were named honorees for a given award, or winners/medalists of the award itself. *p<0.1; **p<0.05; ***p<0.01

## G Discussion of Computational Content Analysis

In this section, we describe the benefits and limitations of computational content analysis as compared to manual content analysis. We then describe how we used manual content analysis to validate our measures. Finally, we conduct a cost-effectiveness analysis which highlights a key advantage of our approach – far greater reach in terms of the ability to measure representation in an entire book, to respond nimbly to changes in analysis plans, and significantly lower cost.

### G.A Benefits of Computational Content Analysis

*Improved speed and reduced cost allow the study of more books.* First, computational content analysis can be used to systematically analyze features in large bodies of content in a short amount of time. Due to their size, these bodies of content were previously beyond the reach of traditional manual content analysis. Using computational tools, we characterize the representation of all detected gendered terms, named characters, and pictured characters detected in over 1,100 books. This is one or two orders of magnitude larger than most prior studies. Further computational analysis of even larger collections of books would incur minimal additional cost beyond the digitization of the material.

*Greater scope for measurement within each book.* Computational tools are able to measure more sites of representation in each book. This includes both the ability to analyze all pictured and named characters detected in the book's images and text – as opposed to just the main characters, as is common in much manual content analysis (e.g., Koss 2015; Krippendorff 2018) – and to analyze a wider variety of features of each character. By contrast, resource constraints limit the number of characters and dimensions of representation that can be measured using manual analysis. Studies that use manual content analysis on a larger sample explicitly indicate compensating for the cost implications of so doing by focusing on a smaller number of prominent features, such as the book's title, the images on its cover, and/or the identities of only the main characters (Koss, 2015; Koss, Johnson and Martinez, 2018).

*Greater flexibility and scalability.* Separate from scope, our approach has the benefit of yielding greater flexibility and scalability. In a given study, if re-analysis or new analysis is required after the initial coding, the fixed costs of identifying, hiring, and training coders are again incurred. In computational content analysis, the only additional costs are the costs of digitizing material, the computational power necessary to re-run the analysis, and human input to adjust the code. Our approach avoids these and other related costs, allows for greater flexibility in expanding or changing a study's scope mid-stream, either by adding dimensions of analysis within books, or by adding additional content.

*Reliability.* In manual content analysis, inter-rater reliability is a core concern which increases with scale (Neuendorf, 2016; Krippendorff, 2018).[4] In computer-driven analysis, however, these concerns do not vary with scale, as the traits of the coder are held constant.

[4] Once the AI is trained, it conducts its analysis with the same level of replicability, irrespective of scale. In manual content analysis, the cost of maintaining reliability of raters increases as the number of raters increases, as it incurs additional costs of training and supervision to ensure fidelity.

### G.B Cost-Effectiveness

Next, we describe our work to validate our tools using manual content analysis. Drawing from validation theory, we conducted traditional manual content analysis to give us an estimate of input needs and costs for a basic cost-effectiveness analysis, and to validate our measures (Kane, 2013; Neuendorf, 2016). To do so, we hand-coded representations in 30 short stories and poems for children written and illustrated by a variety of authors and illustrators from a third grade reading textbook published in 1987.

It took human coders approximately 40 hours to code the entire book (400 pages at an average of 6 minutes per page).[5] While the length of time needed to code "by hand" varies with the grade level of the books in our sample, we estimate that it would have taken us over 16,000 hours to hand-code the 162,872 pages in our sample of children's books. At an hourly wage of between \$15 and \$20, we estimate this work would have cost between \$244,000 to \$326,000.

### G.C AI is Only Human

Measuring representation in content via any means will generate some errors in measurement. In traditional content analysis, analysts may misclassify some images or text. If this occurs at random, this can be treated as standard measurement error, which would be captured via estimating inter-rater reliability (Neuendorf, 2016; Krippendorff, 2018). If, however, traits of the analyst systematically influence their coding, then error from misclassification may be non-classical, leading to a bias in expectation (Krippendorff, 1980). This can arise, for example, if an analyst's identity (e.g., one's race and/or gender) causes them to classify content differently than analysts of different identities (Boer, Hanke and He, 2018).

These same biases appear in AI models. Many AI models, including those we use, are trained using a set of data which are first labeled by humans. Furthermore, nearly all models are either fine-tuned, evaluated, or both, based on their performance relative to human classification. As a result, the bias in classical content analysis is "baked into the pie" for computer-driven content analysis (Das, Dantcheva and Bremond, 2018).

Most face detection models are trained using photographs of humans – particularly White humans – which could lead us to undercount people of color and illustrated characters if the model were less able to identify characters on which it was not trained (Buolamwini and Gebru, 2018). To address this, we trained our own face detection model using 5,403 illustrated faces from the Caldecott and Newbery corpora (discussed in Section IV.A.1). A similar problem with under-detection of certain types of faces could also appear in the skin segmentation process, as we relied upon a series of convolutional neural networks to identify skin, rather than on manual (i.e., human-performed) identification of the skin region of faces.

These issues persist when classifying features. In the case of gender, for example, all public data sets with labels for gender that we encountered have a binary structure, limiting classification to "female" or "male," and neglecting to account for gender fluidity or

[5]Hand-coding of pages entails documenting a wide variety of features in image and, separately, text, which is a time- and detail-intensive process. Our estimate of six minutes per page represents a lower bound on the time needed to perform the type of analysis we conducted. In this case, for example, the manual coders did not count every token that could be related to gender, nationality, and color.

nonbinary identities. Furthermore, intrinsic to these models is the general assumption that we can predict someone's gender identity using an image of their faces (Leslie, 2020). Similar problems beset the task of classifying putative race (Fu, He and Hou, 2014; Nagpal et al., 2019; Krishnan, Almadan and Rattani, 2020). Resolving these problems is an active field of inquiry, and recent scholarship has suggested several promising paths forward for doing so (Buolamwini and Gebru, 2018; Mitchell et al., 2019).

While AI is a product of and therefore reflects human biases, human biases are also intrinsic to traditional "by-hand" content analysis. Manual coding necessarily reflect the biases of the individual coders. We observed that the identities of the manual labelers on our team led to non-classical measurement error, particularly in the classification of race of the pictured characters in images. We therefore use multiple measures for each identity to try to understand the extent of this potential error in classification. For example, in addition to the manually coded putative race of famous figures, we examine also examine skin color of detected characters.

While we primarily use AI tools to study representation, we end this section by emphasizing that AI and manual coding provide complementary understanding of content. The tools we use are meant to rapidly estimate how a human might categorize these phenomena. They are motivated by human perception and, ultimately, their performance is also evaluated based on how accurately they can determine how a human might perceive the representations in images and text. Our use of these tools depends on human input at each stage, from the conception of tools and the labelling of training data, to the evaluation of the tools' accuracy and the way that we interpret their results. We see our efforts adding the strengths of recent advances in computational science to content analysis as a natural extension of the rich history of human-driven analysis in this field.

### G.D Validation

The hand-coding of representations in 30 short stories and poems for children that we discuss in the previous section also helps us evaluate the plausibility of our measures and also identify messages our tools failed to detect, clarifying limitations of computer-led content analysis. Regardless of whether we use manual coding or computer vision, the broad patterns we find are similar. Over 50 percent of the characters/detected faces and gendered words are male and the skin colors depicted are skewed away from darker-skinned individuals.

## H Methods Appendix

In this appendix, we provide greater detail on our methods for converting images and text, respectively, into data.

### H.A Images as Data

In this section, we describe our methods for converting images into analyzable data on skin color, race, gender, and age.

#### H.A.1 Image Feature Classification: Face Detection Methods

To train our face detection model, we split our manually labeled data set into training (80 percent of the data), validation (10 percent of the data, used for hyper-parameter tuning), and testing (10 percent of the data, used for evaluating the model).[6]

The manually labeled test data are kept separate from the training and hyper-parameter tuning algorithms.[7] The models compare results from the algorithms to the manual labels in the test data to evaluate the accuracy of the algorithms.

We use two specific parameters that are commonly used to evaluate the performance of this class of model: "precision" and "recall."[8] Precision is the proportion of items which are correctly assigned a label out of all items that *are assigned* that label. For example, precision for detected faces is the number of actual faces out of all regions in an image that our model classifies as a face (that might not always be a face). Recall, on the other hand, measures the percentage of items that are correctly assigned a label out of all items that *should be assigned* that label. In the case of recall for faces, recall is the number of correctly detected faces as a proportion of the actual number of faces in the book.[9] Formally:

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

$$recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

The higher the precision, the fewer false positives the model produces. In other words, precision measures the following proportion: among the test examples that were predicted with a certain label, which are truly of that label? On the other hand, the higher the recall,

[6] The validation data are used for hyper-parameter tuning to optimize the model architecture. Hyper-parameter tuning involves "searching" for the optimal values of the hyper-parameters. Examples of hyper-parameters include learning rate, number of epochs (number of times the model goes through the whole data set), and different activation functions of the model that can be tuned to improve the accuracy of the model. FDAI is using Google Cloud infrastructure and functions to test different hyperparameter configurations and chooses the set of hyperparameters that maximize the model's accuracy.

[7] The manually labeled data for the face detection model came from data labeled by our research team. The manually labeled data for the feature classification model came from the UTKFace data set.

[8] AutoML has its own functions to calculate the precision and recall of the model. For our purposes, we use the precision and recall that were calculated on the test data. In other words, the model is run on the test data, and then the results generated by the trained model are compared to the results from the manually labeled test data.

[9] Sometimes "recall" is also referred to as "sensitivity."

the fewer false negatives the model produces. In other words, recall tells us, from all the test examples that should have had the label assigned, how many were actually assigned the label (Sokolova and Lapalme, 2009). Our face detection model has 93.4 percent precision and 76.8 percent recall.

### H.A.2 Image Feature Classification: Skin Segmentation Methods

Traditional skin segmentation methods assign a skin or non-skin label for every pixel of the cropped face image in which skin features are extracted. These labels are assigned using traditional image processing methods such as thresholding, level tracing, or watershed. These methods, however, face a number of challenges such as the need to take into account skin color (in)consistency across variations in illumination, acquisition types, ethnicity, geometric transformations, and partial occlusions (Lumini and Nanni, 2020). Our FC-CNN CRF method – by combining three different types of networks (an unary network, a pairwise network, and a continuous CRF network) – takes into account the local and global dependencies between the pixels, and considers the location of the pixels when assigning the skin label, preserving the region integrity.[10] The CRF model parses the face image into semantic regions (e.g, eyes, eyebrows, and mouth) for further processing. This is integrated with an unary network for generating the feature map. The pairwise network is then used to learn the pixel-wise similarity based on neighbor pixels. Thus segmentation accuracy is greatly improved compared to traditional pixel-wise methods which do not take into account semantic regions, boundaries, and the correlations between neighbor pixels. Note that even though we detect over 54,000 faces in our sample of children's books, we are only able to obtain usable skin segmentation for 81 percent of the faces. This is because the CNN-based skin segmentation approach we use does not work on all illustrated faces.

### H.A.3 Image Feature Classification: Classifiying Skin Color Types

We classify the representative skin color for each detected face into one of three categories of skin color type: (1) monochromatic skin colors (e.g., grayscale, sepia), (2) polychromatic human skin colors (e.g., brown, beige), and (3) polychromatic non-typical skin colors (e.g., blue, green).

**Monochromatic Classification.** In the RGB color space, the closer the R, G, and B values are to each other, the less vibrant the color. For this reason, we classify a face as monochromatic if the standard deviation between the R, G, and B values associated with the weighted average of the face's top $k$ skin colors is less than a threshold $T$. Thus, a given face $i$ is classified as monochromatic using the following equation:

$$\text{(FI)} \qquad Monochromatic_i = \mathbb{1}\left[\sqrt{\frac{(R_i-\mu_i)^2+(G_i-\mu_i)^2+(B_i-\mu_i)^2}{3}} <= T\right]$$

Where $\mu_i$ is equal to the average of the R, G, B values of face $i$.

Our process of choosing a threshold $T$ proceeded as follows. First, we manually labeled a random sample of 2,836 detected faces (stratified by collection) as either monochromatic or polychromatic. We then calculated the mean squared error between the manual label and our

[10]Conditional random field (CRF) is a class of statistical modeling using a probabilistic graphical model.

predicted labels using the equation above for every integer value of $T$ between zero and 100. We calculated the average of these mean squared errors using 1,000 bootstrapped samples. The threshold that minimized the mean squared error on average is given by this provides a classification of images as being monochromatic or not that is 82.9 percent accurate, on average.

**Polychromatic Classification.** Once we have identified the monochromatic faces, we then separate the remaining faces into two polychromatic color types using the R, G, and B values associated with the weighted average of a face's top $k$ skin colors: (1) human skin colors and (2) polychromatic non-typical skin colors. This allows us to distinguish between humans and non-human characters who may have colorful skin tints (e.g., aliens, monsters, or characters found in Dr. Seuss books). Specifically, we classify the skin color of the face as a typical human skin color if R $\geq$ G $\geq$ B.[11] Otherwise, it is classified as a polychromatic non-typical skin color.

(FII) $$Human_i = [1 - Monochromatic_i] \times \mathbb{1}\left[R \geq G \geq B\right]$$

(FIII) $$NonTypical_i = [1 - Monochromatic_i] \times [1 - Human_i]$$

We find this method of classifying the skin color of a face as human or non-typical to be 82.1 percent accurate using our set of 2,836 manually labeled faces.

To classify the darkness or lightness of pictured skin colors, we use the perceptual tint, or L* value, associated with the average of the $k$ colors in L*a*b* space. This value ranges from zero to 100 where a value of zero represents the color black and a value of 100 represents the color white, and there is a range of colors in between.

### H.A.4 Image Feature Classification: Race, Gender, and Age

To train our feature classification model we use a publicly available labeled data set called UTKFace which is a large-scale face data set consisting of over 20,000 face images with age, gender, and ethnicity labels. The images cover large variation in pose, facial expression, illumination, occlusion, and resolution and cover a large age range of individuals (from 0 - 116 years old) (Zhang, Song and Qi, 2017). We split this data set into three parts: training (80 percent of the data), validation (10 percent), and testing (10 percent). The resulting model has 90.6 percent precision and 88.98 percent recall in our testing data.

*Race Classification (Images).* The model assigns the probability that a detected face is of a given race category: Asian, Black, Latinx + Others, or White. The race labels in the original model were defined in the UTKFace data set and include: Asian, Black, Indian, Others (where "Others" includes Latinx and Middle Eastern) and White. We combine Asian and Indian predictions into a broader Asian category. Each identified face is assigned the

[11]The boundaries of skin color regions in RGB space from an established pixel-based method of skin classification are defined as $R > 95$ and $G > 40$ and $B > 20$ and $\max\{R, G, B\} - \min\{R, G, B\} > 15$ and $|R - G| > 15$ and $R > G$ and $R > B$ (Vezhnevets, Sazonov and Andreeva, 2003). However, these rules for defining skin color regions are only focused on classifying skin color from photographs. We expand this region in RGB space to account for illustrated skin colors (such as pure white and yellow).

race category to which the model gives the highest predicted probability.[12]

*Gender Classification (Images).* For each face detected, we predict the probability that the face is female- (or male-) presenting. We label a face as female if the predicted probability that the face is female-presenting is greater than 50 percent; otherwise, we label the face as male.

We recognize that these classifications are imperfect and focus only on the performative aspect of gender presentation, as they are trained based on how humans classify images. Future work should incorporate the classification of fluid and nonbinary gender identities.

*Age Classification (Images).* The model assigns the probability that a detected face is of a given age category (infant, child, teenager, adult, senior). We aggregate these categories into two bins: child and adult. We collapse the probabilities for infant and child into a single "child" bin and those for teenager, adult, and senior into a single "adult" bin. A face is classified as that of a child if the probability assigned to the age categories comprising the aggregated child bin is greater than 50 percent, and as that of an adult otherwise.

### H.B Text as Data

In this section, we provide greater detail on the tools we use to turn text from books into analyzable data on race, gender, and age.

#### H.B.1 Digitizing Text

To extract text from digital scans of books, we use the Google Vision Optical Character Recognition (GVOCR). We input the raw files into GVOCR, which identifies and separates the text in each file from the images (e.g., illustrations and photographs). It then applies its own OCR software to the text sections of the scans, converting the text into ASCII which then encodes each character to be recognized by the computer. This generates the text data we analyze.[13]

We clean these raw text data to remove erroneous characters and other noise generated by the OCR process, increasing the precision of our measurement of features in the text.

[12] Classifying race is an imperfect exercise that will yield imperfect algorithms with imperfect categories. Our analysis by race looks across collections within race, so any error within a race would be consistent across collections (i.e., Both the Mainstream and Diversity collections would classify people of the same race similarly.) We describe related issues in the body of the manuscript as well.

[13] There are other commonly used OCR interfaces. However, over the past five years, researchers have consistently identified Google Cloud Vision OCR as the best technology for converting images to text. In one study, Tafti et al. (2016) compare the accuracy of Google Docs (now Google Vision), Tesseract, ABBYY FineReader, and Transym OCR methods for over 1,000 images and 15 image categories, and found that Google Vision generally outperformed other methods. In particular, Google Vision's accuracy with digital images was 4 percent better than any other method. Additionally, the standard deviation of accuracy for Google Vision was quite low, suggesting that the quality of OCR does not drastically change from one image to the next. A test of OCR tools by programmers compared the performance of seven different OCR tools (Han and Hickman, 2019). This analysis also found Google Vision to be superior, specifically when extracting results from low resolution images. In another study that focused on comparing results from multiple image formats (including .jpg, .png, and .tif), Vijayarani and Sakila (2015) found that Google surpassed all other OCR tools. We also tested OCR using ABBYY FineReader and Google Tesseract. Our comparison of their performance relative to manual coding also showed GVOCR performed the best.

The cleaning process removes numerical digits and line breaks but maintains capitalization, punctuation, and special characters. It also standardizes the various permutations of famous names (e.g., all variations of reference to Dr. Martin Luther King Jr. become "Martin Luther King Junior").

### H.B.2 Predicting Gender from Character First Names

To identify the gender of characters not identified as famous, we extract the first name of each non-famous named entity that is tagged as a person by the spaCy NER engine and estimate the probability that the character is female using data on the frequency of names by gender in the U.S. population from the Social Security Administration. Our sample of "relevant" Social Security data include only data from years which overlap with the years in our sample of children's data.

If the predicted probability that a character is female is greater than 50 percent, we label that character as female. Otherwise, the character is labeled as male.[14] To test how accurate these predictions are, we predicted the gender of each famous person in our data using their first names and compared these predictions to their gender identified using Wikipedia and found that our predictions were 96 percent accurate. We do not classify race using first names only. Other recent text analysis has shown that conventional methods for classifying race using first names only fail to accurately distinguish between Black people and White people (Garg et al., 2018).

We are not able to make a prediction for the remaining named entities. For example, characters such as "New Yorker" which the spaCy NER engine identified and labeled as a person will not receive a prediction because "New" does not appear as a first name in Social Security data.

### H.B.3 Vocabulary Lists Used in Token Counts

The vocabulary lists containing all the words we use in our token counts are listed below. These lists were compiled as the best set of reasonable vocabulary to capture the constructs we study. While they are larger than vocabulary lists from other recent efforts in Natural Language Processing, they nonetheless are unlikely to be a comprehensive list of all English words relevant to a given construct (Caliskan, Bryson and Narayanan, 2017).

**Gendered Terms.** The gendered terms we enumerate are as follows.

***Female.*** abuela, abuelita, actress, aunt, auntie, aunties, aunts, aunty, czarina, damsel, damsels, daughter, daughters, emperess, emperesses, empress, empresses, fairies, fairy, female, females, girl, girls, grandma, grandmas, grandmom, grandmother, grandmothers, her, hers, herself, housekeeper, housekeepers, ladies, lady, ma'am, madame, mademoiselle, mademoiselles, maid, maiden, maidens, maids, mama, mamas, mermaid, mermaids, miss, mlle, mme, mom, mommies, mommy, moms, mother, mothers, mrs, ms, nana, nanas, princess, princesses, queen, queens, she, sissie, sissy, sister, sisters, stepmother, stepmothers, titi, tsarevna, tsarina, tsaritsa, tzaritza, waitress, wife, witch, witches, wives, woman, women

***Plural Female.*** aunties, aunts, damsels, daughters, emperesses, empresses, fairies,

[14] We predict gender with the *gender* package available in R which uses Social Security Administration data (Mullen, 2020).

females, girls, grandmas, grandmothers, housekeepers, ladies, mademoiselles, maidens, maids, mamas, mermaids, mommies, moms, mothers, nanas, queens, sisters, stepmothers, witches, wives, women

***Singular Female.*** abuela, abuelita, aunt, auntie, aunty, czarina, damsel, daughter, emperess, empress, fairy, female, girl, grandma, grandmom, grandmother, her, hers, herself, housekeeper, lady, maam, madame, mademoiselle, maid, maiden, mama, mermaid, miss, mlle, mme, mom, mommy, mother, mrs, ms, nana, princess, queen, she, sissie, sissy, sister, stepmother, titi, tsarevna, tsarina, tsaritsa, tzaritza, wife, witch, woman

***Young Female.*** damsel, damsels, daughter, daughters, fairies, fairy, girl, girls, mademoiselle, mademoiselles, maiden, maidens, miss, princess, princesses, tsarevna

***Old Female.*** abuela, abuelita, aunt, auntie, Auntie, aunts, aunty, czarina, emperess, emperesses, empress, empresses, grandma, grandmas, grandmom, grandmother, grandmothers, housekeeper, housekeepers, maam, madame, mama, mamas, mlle, mme, mom, mommies, mommy, moms, mother, mothers, mrs, nana, nanas, queen, queens, stepmother, stepmothers, titi, tsarina, tsaritsa, tzaritza, wife, witch, witches, wives, woman, women

***Male.*** abuelito, abuelo, actor, boy, boys, bro, brother, brothers, butler, butlers, chap, chaps, czar, dad, daddies, daddy, dads, einstein, emperor, emperors, father, fathers, fellow, fellows, gentleman, gentlemen, granddad, granddads, grandfather, grandfathers, grandpa, grandpas, he, him, himself, his, hisself, husband, husbands, king, kings, knight, lad, lads, lord, lords, male, males, man, master, masters, men, merman, mermen, mr, paige, paiges, papa, papas, prince, princes, sir, sirs, son, sons, squire, squires, stepfather, stepfathers, tio, tsar, uncle, uncles, waiter, wizard, wizards

***Plural Male.*** boys, brothers, butlers, chaps, daddies, dads, emperors, fathers, fellows, gentlemen, granddads, grandfathers, grandpas, husbands, kings, knights, lads, lords, males, masters, men, mermen, paiges, papas, princes, sirs, sons, squires, stepfathers, uncles, wizards

***Singular Male.*** abuelito, abuelo, boy, bro, brother, butler, chap, czar, dad, daddy, emperor, father, fellow, gentleman, granddad, grandfather, grandpa, he, him, himself, his, hisself, husband, king, knight, lad, lord, male, man, master, merman, mr, paige, papa, prince, sir, son, stepfather, tio, tsar, uncle, wizard

***Young Male.*** boy, boys, lad, lads, prince, princes, son, sons

***Old Male.*** abuelito, abuelo, butler, butlers, czar, dad, daddies, daddy, dads, emperor, emperors, father, fathers, gentleman, gentlemen, granddad, granddads, grandfather, grandfathers, grandpa, grandpas, husband, husbands, king, kings, lord, lords, man, men, mr, papa, papas, sir, sirs, stepfather, stepfathers, tio, tsar, uncle, uncles, wizard, wizards

## I Limitations of the Economic Analysis

In this section, we discuss some limitations of our investigation of the economic forces from Section VI behind the levels of representation we find.

The first limitation of this investigation is that it is descriptive, rather than causal, and exploratory, rather than confirmatory. We conduct and report a series of descriptive analyses of relationships in the cross-section and over time. We anticipate that the stylized facts we present will be hypothesis-generating, instigating further work to characterize these relationships with experimental, quasi-experimental, and structural methods.

A second limitation is that there exist a series of potential contributors to the results analyzed in this section beyond the supply and demand forces explored above. Our analysis attempts to characterize and investigate evidence for forces that influence what consumers *choose* to purchase. We do not explore factors that may influence what consumers *choose not* to purchase; for example, there is scope for for discrimination against certain identities to drive some of these results. This force could exert itself on the decisions of purchasers, publishers, and awards committees. Its impact would be in addition to – but separate from – the forces we explicitly explore.

Another related limitation is a potential market response from publishers to the preferences of different award-granting committees. There is necessarily a limited number of books that can receive major awards. If these major awards increase consumption of books that receive those awards, publishers may actively try to produce books that are more likely to receive these awards, reinforcing whatever patterns of representation that publishers perceive the relevant awards committee to prefer. Because membership on awards committees is confidential, analysis of their preferences beyond what we present here exceeds the reach of our study.

Separately, we observe that the effect of utility from homophily is attenuated for book purchasers who are not White, in comparison to White purchasers. We attribute this, in part, to status-quo bias. We acknowledge, however, that part of this pattern may also arise because of the higher costs associated with consuming books that highlight characters with non-dominant identities. These higher costs could arise from at least two sources – financial and psychic – which we cannot fully disentangle. The first source may be increased financial cost stemming from there being fewer options available in the larger market centering non-dominant identities, leading to a higher price (i.e., pricing-in diversity). We provide evidence of this in our economic analysis of supply-side factors. The second source may be from increased psychic costs given that the demand for homophily by members of the dominant group may be amplified by status-quo bias, while this may not be the case for other groups.

Additionally, our empirical analysis of the relationship between content and consumer demographics is limited to the content in award-winning books. In Section II, we document that these awards are strongly correlated with what is purchased and consumed in homes, libraries, and schools. While we might wish to draw from a representative sample of the "universe" of children's books, this group is less well-defined and likely has lower per-book influence than books in our analysis sample. One related challenge is how to appropriately account for the award itself influencing consumer preferences.

Finally, our findings related to skin color can not be further explained in the scope of our economic analysis. We do not have skin color information for individuals in the larger population, so we can not examine the relationship between consumer skin color and revealed preference related to content. These are important phenomena to document nonetheless, given the importance of the role that the messages in these books play in potentially shaping children's development. We leave exploration of their potential causes to future research.

## J Perspectives of Suppliers of Children's Books

We complement our quantitative analysis of the supply and demand pressures on publishers' choice of books with qualitative analysis of data from semi-structured, one-on-one interviews of professionals who currently work at or recently worked at libraries, publishing houses, and children's bookstores, and/or who served on award selection committees. Our interviews began with a prompt that asked a series of questions, first about the processes the person used to identify and select books, and then about their perception and understanding of the forces that shape the content of these books.

A few key themes arose from these conversations. The first theme is that many booksellers, publishers, and librarians wish to procure and promote books that highlight people from historically marginalized groups, particularly Black and Latina/o/x people. A common goal across librarians and booksellers was the desire to show children both potential versions of themselves, as well as potential versions of the world they will grow up to inhabit. One professional who had served as both a librarian and a bookseller asserted that, when presenting books to children, librarians and booksellers alike wish "to provide each child with both a mirror and a window." This paraphrases the description in Bishop (1990), which argues that the books we give to children should serve as mirrors, windows, and sliding glass doors - in other words, the books should show children visions of themselves, windows onto the reality they inhabit, and doors through which they can step to see imaginary futures they might inhabit, respectively.

The second theme is that, until recently, this desire to present children with both a mirror and a window was very difficult to meet. Several interviewees asserted that this difficulty arose from mainstream publishers not offering sufficient amounts of this content. This corresponds to the economic forces we study in Section VI, wherein books with greater representation of non-dominant societal groups will be under-supplied by the market. One interviewee – the owner of a decades-old children's bookstore in a medium-sized midwestern city – lamented that before the mid-2010's, requests to publishers for books representing people of color was met with the quip: "we don't sell those books because those books don't sell." In response, motivated booksellers such as this professional sought out smaller publishers specializing in such content, such as Lee and Low, a publishing house founded in 1991 to address this shortcoming.[15]

To better understand the process through which books were selected for these awards, we also conducted semi-structured interviews with people involved in the selection committees. Committee members are selected by either election or appointment by the head of ALSC to serve for a one-year term. Committee members review books published in that year, vetting them based on a set of criteria specific to each award. At the end of the term, the committee convenes to discuss candidates and select honorees. Two key themes arose in these discussions: first, the criteria for selection are stable over time, despite the other secular changes in this period.[16] Second, the composition of the award committees generally

[15] The #WeNeedDiverseBooks movement (diversebooks.org), started in roughly 2012, has also agitated and organized for more equitable representation in books. A relevant resource created to meet this need is the Diverse Book Finder, available at diversebookfinder.org.

[16] We give these criteria for the Mainstream collection awards, and link to those in the Diversity collection,

comprise a circulating group of librarians, booksellers, and educators that refreshes every year.[17] As a result, these awards – particularly those in the Mainstream collection – are likely to reflect the equilibrium of supply from the publishing industry and demand from the annually rotating group of educators and booksellers selected to be on the committees, rather than the idiosyncratic tastes of a few individuals.

in Appendix D.

[17]According to ALSC bylaws for the Mainstream awards, individuals who served on a committee in one year were ineligible to serve on it in following several years.

## Appendix References


**Boer, Diana, Katja Hanke, and Jia He.** 2018. "On detecting systematic measurement error in cross-cultural research: A review and critical reflection on equivalence and invariance tests." Journal of Cross-Cultural Psychology, 49(5): 713–734.

**Buolamwini, Joy, and Timnit Gebru.** 2018. "Gender shades: Intersectional accuracy disparities in commercial gender classification." Conference on Fairness, Accountability and Transparency, 77–91.

**Das, Abhijit, Antitza Dantcheva, and Francois Bremond.** 2018. "Mitigating bias in gender, age and ethnicity classification: a multi-task convolution neural network approach." Proceedings of the European Conference on Computer Vision (ECCV) Workshops.

**Fu, Siyao, Haibo He, and Zeng-Guang Hou.** 2014. "Learning race from face: A survey." IEEE Transactions on Pattern Analysis and Machine Intelligence, 36(12): 2483–2509.

**Han, Ted, and Amanda Hickman.** 2019. "Our search for the best OCR tool, and what we found." Accessed March 10, 2021.

**Krippendorff, Klaus.** 1980. "Validity in content analysis." In Computerstrategien fÃr die kommunikationsanalyse. . 1 ed., , ed. E. Mochmann, 69–112. Frankfurt, Germany:Campus Verlag.

**Krippendorff, Klaus.** 2018. Content Analysis: An Introduction to its Methodology. Sage publications.

**Krishnan, Anoop, Ali Almadan, and Ajita Rattani.** 2020. "Understanding fairness of gender classification algorithms across gender-race groups." arXiv.

**Leslie, David.** 2020. "Understanding bias in facial recognition technologies: An explainer." The Alan Turing Institute.

**Lumini, Alessandra, and Loris Nanni.** 2020. "Fair comparison of skin detection approaches on publicly available datasets." Expert Systems with Applications, 160: 113677.

**Mitchell, Margaret, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru.** 2019. "Model cards for model reporting." Proceedings of the Conference on Fairness, Accountability, and Transparency, 220–229.

**Mullen, Lincoln.** 2020. "gender: Predict gender from names using historical data." R package version 0.5.4.

**Nagpal, Shruti, Maneet Singh, Richa Singh, and Mayank Vatsa.** 2019. "Deep learning for face recognition: Pride or prejudiced?" arXiv.

**Neuendorf, Kimberly A.** 2016. The Content Analysis Guidebook. Sage.

**Sokolova, Marina, and Guy Lapalme.** 2009. "A systematic analysis of performance measures for classification tasks." Information Processing & Management, 45(4): 427–437.

**Tafti, Ahmad P, Ahmadreza Baghaie, Mehdi Assefi, Hamid R Arabnia, Zeyun Yu, and Peggy Peissig.** 2016. "OCR as a service: An experimental evaluation of Google Docs OCR, Tesseract, ABBYY FineReader, and Transym." International Symposium on Visual Computing, 735–746.

**Vezhnevets, Vladimir, Vassili Sazonov, and Alla Andreeva.** 2003. "A survey on pixel-based skin color detection techniques." Moscow, Russia.

**Vijayarani, S, and A Sakila.** 2015. "Performance comparison of OCR tools." International Journal of UbiComp (IJU), 6(3): 19–30.

**Zhang, Zhifei, Yang Song, and Hairong Qi.** 2017. "Age progression/regression by conditional adversarial autoencoder." IEEE Conference on Computer Vision and Pattern Recognition (CVPR).