What we teach about race and gender: Representation in images and text of children's books*

Anjali Adukia
University of Chicago and NBER

Alex Eble
Columbia University

Emileigh Harrison
University of Chicago

Hakizumwami Birali Runesha
University of Chicago

Teodora Szasz
University of Chicago

July 29, 2021

Abstract

Books shape how children learn about society and social norms, in part through the representation of different characters. To better understand the messages children encounter in books, we introduce new artificial intelligence methods for systematically converting images into data. We apply these image tools, along with established text analysis methods, to measure the representation of race, gender, and age in children's books commonly found in US schools and homes over the last century. We find that more characters with darker skin color appear over time, but "mainstream" award-winning books, which are twice as likely to be checked out from libraries, persistently depict more lighter-skinned characters even after conditioning on perceived race. Across all books, children are depicted with lighter skin than adults. Over time, females are increasingly present but are more represented in images than in text, suggesting greater symbolic inclusion in pictures than substantive inclusion in stories. Relative to their growing share of the US population, Black and Latinx people are underrepresented in the mainstream collection; males, particularly White males, are persistently overrepresented. Our data provide a view into the "black box" of education through children's books in US schools and homes, highlighting what has changed and what has endured.

*Contact: team@miielab.com, (adukia, harrisone, runesha, tszasz)@uchicago.edu, eble@tc.columbia.edu.
For helpful feedback, we thank Barbara Atkin, Karen Baicker, Anna Brailovsky, Tom Brock, Steven Durlauf, Alice Eagly, Allyson Ettinger, James Evans, Adam Gamoran, Jon Guryan, Andrew Ho, Rick Hornbeck, Caroline Hoxby, Susanna Loeb, Jens Ludwig, Jonathan Meer, Martha Minow, Sendhil Mullainathan, Derek Neal, Anna Neumann, Aaron Pallas, Steve Raudenbush, Cybele Raver, Heather Sarsons, Fred Stafford, Chenhao Tan, David Uminsky, Miguel Urquiola, Alessandra Voena, Amy Stuart Wells, and others including seminar participants at AEFP, CGD, EPC, Harvard Measurement Lab, NAEd/Spencer, NBER, W.T. Grant Fdn., UChicago, UVA, and UW-Madison. For financial support, we thank UChicago BFI, UChicago CDAC, NAEd/Spencer, and UChicago Career Advancement. The research reported here was also supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A200478 to the University of Chicago. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education. For excellent research assistance, we thank Fabiola Alba-Vivar, Celia Anderson, Ryan Atkinson, Callista Christ, Marliese Dalton, Anjali Das, Maya Escueta, Saloni Gupta, Amara Haider, Shavonna Hinton, Camilo Ibáñez, Juan Miguel Jimenez, Jalnidh Kaur, Zipporah Klain, Jarvis Lam, Erica Lin, Ping-Chang Lin, Ping-Jung Liu, Simon Mahns, Noah McLean, Karla Monteiro, Ifeatu Oliobi, Raj Shukla, Bhargavi Thakur, Jeffrey Tharsen, Qurat ul ain, and Charlie Wang. We also thank Ashiyana and Kairav Adukia-Hornbeck for manual coding assistance. For access to important resources, we thank UChicago RCC, LaShanda Howard-Curry, Bridget Madden, and Kalli Mathios.

Education teaches children about the world, its people, and their place in it. Much of this happens through the curricular materials society presents to children, particularly in the books they read in school and at home (Giroux, 1981; Apple and Christian-Smith, 1991; Jansen, 1997; Van Kleeck, Stahl and Bauer, 2003; Steele, 2010). These lessons are conveyed, in part, through the inclusion or exclusion of characters of different identities in the images and text of books. The presence or absence of these characters contributes to how children see themselves and others, their strengths, and their possible futures. Given persistent racial and gender inequality in society (Darity and Mason, 1998; O'Flaherty, 2015; Blau and Kahn, 2017; Quillian et al., 2017), and the potential importance of identity and representation in contributing to beliefs, aspirations, academic effort, and outcomes (Dee, 2005; Riley, 2017; Gershenson et al., 2018; Porter and Serra, 2020), these representations offer means through which society can either address, perpetuate, or entrench structural inequalities.

In this paper, we use new image tools and established text tools to measure the representation of racial constructs, gender identity, and age in the images and text contained in influential collections of children's books. First, we develop and showcase new tools for the systematic analysis of images, highlighting their potential use in a wide range of applications in policy, education practice, and social science research. Second, we apply these image tools, alongside established text analysis methods, to systematically characterize representation in ways that computers could not have previously done for children's books, particularly related to measuring the skin color, racial identity, gender presentation, and age of pictured characters.

Our main data set is a series of books targeted to children and likely to appear in homes, classrooms, and school libraries over the past century. Specifically, we use books that have won awards from the Association for Library Service to Children, a division of the American Library Association, starting in 1922. These and other children's books are often filled with images that transmit implicit and explicit messages to readers. Historically, content analysis to measure these messages has been done "by hand" using human coders (Bell, 2001; Neuendorf, 2016; Krippendorff, 2018). Such analysis provides deep understanding but can generally only be done on a small set of content and necessarily reflects human behavior and biases. We apply and develop computer vision tools that use convolutional neural networks to identify and classify components of images; in our case, the tools detect characters in photos and illustrations and classify their skin color, race, gender, and age.[1] While artificial intelligence tools also reflect bias in their training data and algorithms, they

[1]Convolutional neural networks, or CNNs, are programs trained to model the way the human brain functions by being given examples and then learning to perform tasks (such as detecting faces or classifying features on these faces) by analyzing these examples without explicit instructions.

can be standardized, are more replicable, and can be applied to a much larger sample than manual content analysis permits. These books also represent an ideal setting for demonstrating both the challenges of analyzing heterogeneous types of images and our tools' ability to process them into usable data.[2]

Analyzing images involves three primary components: (1) training the computer to detect faces, (2) classifying skin color, and (3) predicting the race, gender, and age of the faces. We build on existing face analysis software tools, making some key improvements. First, because most established face detection models are trained on photographs, and because the books in our sample contain a large number of illustrations, we trained our own model using illustrated faces to improve accuracy. Second, we developed a model to classify skin color of faces.[3] This process involves isolating the skin of the detected face using convolutional neural networks, identifying the predominant colors in that segmented skin using k-means clustering, and then using a weighted average of those colors to classify the skin color of a character. Third, we train a new model with higher precision in its classification of race, gender, and age than in previously available models.

The second contribution of this paper is to use these image tools, in conjunction with existing text analysis tools, to understand the representations of race, gender, and age seen by the generations of children exposed to these books, and how this has changed over time. We divide the award-winning corpora into two primary groups: (i) "Mainstream" books considered to be of high literary value but written without explicit intention to highlight an identity group (i.e., the Newbery and Caldecott Awards) and (ii) "Diversity" books selected because they highlight experiences of specific identity groups (e.g., the Coretta Scott King and Rise Feminist Awards). We first show evidence that suggests these awards matter for readership. Using data from a major public library system, we find that receipt of Mainstream awards is followed by a sustained increase of approximately 100 percent in the likelihood of a book being checked out, relative to other children's books. This corroborates qualitative accounts of how award receipt establishes a book's membership in the "canon" of children's literature (Smith, 2013; Koss, Johnson and Martinez, 2018) and recorded increases in the sales of children's books after receipt of an award (Cockcroft, 2018). This highlights the

[2]Images in children's books, for example, vary widely with respect to several important characteristics. These books can include illustrations or photographs. Images can be polychromatic or monochromatic (e.g., black and white); and even when characters are polychromatic, their skin is sometimes shown in seemingly non-typical colors, such as green or blue. Characters can take human or non-human forms, and images often have shadows or highlights that add to the complexity of measurement of the representation in these images.

[3]Skin color is an important dimension of human categorization for which there exists societal discrimination related to, but distinct from "putative" race, that is, the race that society assigns to people. For example, Hersch (2008) finds that, among legal immigrants to the US, darker skin color is associated with lower wages, even after controlling for demographic and occupational characteristics.

particular influence these books may have and underscores the importance of understanding the messages they may transmit.

We present a series of descriptive analyses documenting patterns of representation in these books over time. Additionally, we explore the efficacy of explicit efforts to highlight diversity and their likelihood to account for intersectional experiences.

We find that books have included more characters with dark skin over time, but those in the Mainstream collection are more likely to depict lighter-skinned characters than those in the Diversity collection, even among characters classified by our model as belonging to a given race. Black and Latinx people are underrepresented in the images and text, relative to their share of the US population. Across all collections, children are more likely than adults to be shown with lighter skin, despite there not being a definitive biological foundation for this systematic difference in skin colors across ages in society.[4] Regardless of the reasons why these differences exist, our estimates show that lighter-skinned children see themselves represented more often in these books than do darker-skinned children.

We also use established text analysis methods to measure the representation of gender, racial constructs, and age in text, complementing our image analysis results. We compare the incidence of female appearances in images to female mentions in text, and we see that females have consistently been more likely to be visualized (seen) in images than mentioned (heard) in the text, except in the collection of books specifically selected to highlight females. This suggests there may be symbolic inclusion of females in pictures without their substantive inclusion in the actual story. Despite being half of the US population, and despite substantial changes in female societal roles over time, females are persistently less likely than males to be represented in both images and text. This finding is consistent across all of the measures we use: predicted gender of the pictured character, pronoun counts, specific gendered tokens,[5] gender of famous characters, character first names, and geographic origin. Another surprising result is that, even though these books are targeted to children, adults are depicted more than children both in images and text.

The Diversity collection has broader geographic representation of famous figures born outside of the United States or Europe than the Mainstream collection. However, when either collection presents a character outside of these two regions, that character is more

[4]Differences in skin color between children and adults could present in many possible configurations: adults could be darker than children (perhaps due to greater exposure to the sun due to outside labor or due to children of mixed race couples being lighter than the average combined skin tone of their parents), children could be darker than adults (given evidence of the breakdown of melanin over the life course (Sarna et al., 2003), or the skin tone of adults and children could be similar, on average.

[5]A "token" refers to a single word such as "queen" or "nephew." We explain this further in Section IV.A.

likely to be male. This suggests that while the Diversity collection may represent a broader range of nationalities, it is still unequal in its representation of identity at the intersection of gender and nationality. Moreover, White males comprise the majority of famous figures in all collections. Famous people from racial groups other than Black people or White people (e.g., Asian, Latinx) are less likely to be represented in any collection, comprising zero to eight percent of all famous people, on average, per collection. Even then, males are generally more likely to be represented than females within each racial group.

Our paper makes two key contributions. First, we develop and hone a series of tools from the field of computer vision for rapidly processing images into analyzable data, and showcase how they can be used to process large amounts of images to study important social phenomena. These tools allow the systematic measurement of characteristics in visual data that were previously beyond the reach of empirical researchers. This contribution is in the spirit of other recent work introducing new sources of data to the economic study of social phenomena, such as text (Gentzkow and Shapiro, 2010; Gentzkow, Shapiro and Taddy, 2019) and geospatial imagery (Burchfield et al., 2006; Henderson, Storeygard and Weil, 2012). Practically, we aim to instigate the use of these tools by scholars in a wide range of fields. This may include, for example, analysis of representation in the historical record, the impacts of visual media such as television programming (Jensen and Oster, 2009; La Ferrara, Chong and Duryea, 2012; Kearney and Levine, 2019), advertising (Bertrand et al., 2010; Lewis and Rao, 2015), and textbooks (Fuchs-Schündeln and Masella, 2016; Cantoni et al., 2017), or linking exposure to different levels of representation with formation of beliefs, preferences, and educational outcomes. This also demonstrates how our tools can be used by another key set of stakeholders: the practitioners, policymakers, and parents looking for information to guide their choice of which books or other curricular materials to include in their classrooms, libraries, and homes.

Second, we show how race, gender, and age have been represented to children in the images and text within influential book collections. This analysis yields three main findings. One, we find multiple sites of "hidden" messages, such as the depiction of children with lighter skin than adults and a greater presence of females being visualized in images than mentioned in the text. Two, we find some evidence that representation is trending towards more parity in both race and gender over time. Three, we find that males and White people are overrepresented in both images and text relative to their shares in the US population. In summary, we find that while some inequality in representation has ameliorated over time, multiple other sites of this inequality persist. These patterns provide a view into the "black box" of education through children's books in US schools and homes, highlighting what has

changed and what has endured.

It is important to note that AI is a product of human biases and therefore necessarily reflects such biases (Das, Dantcheva and Bremond, 2018). Preliminary uses of these models showed that AI classification models can perpetuate inequality caused by these biases (Fu, He and Hou, 2014; Nagpal et al., 2019; Krishnan, Almadan and Rattani, 2020). More recent work has shown how careful application of these models with appropriate reporting can make these biases visible and, in so doing, suggest paths forward – such as deliberate sampling focused on achieving better representation – for minimizing their harms (Buolamwini and Gebru, 2018; Mitchell et al., 2019). Use of our tools, and subsequent improvements upon them, must adhere to these practices in order to prevent retrenchment of such biases.

This paper proceeds as follows. We present background information in Section I. Section II describes the books in our data. Section III explains how we convert images to data on skin color, race, gender, and age. Section IV discusses the text analysis tools. Section V synthesizes our final measures. Section VI presents our main results, showing our estimates of inequality and inclusion of race and gender in the images and text of different book collections, and how these estimates change or persist over time. Section VII discusses the potential benefits and concerns to using AI models. Section VIII discusses the cost-effectiveness of machine-led approaches to analyzing content relative to traditional manual approaches. Section IX concludes.

I The Importance of Representation and the Challenge of Measurement

In this section, we briefly discuss research on the representation of race and gender and follow with a short description of the empirical challenges involved in measuring these representations.

I.A The Importance of Equity in Representation

Our institutional practices, public policies, and cultural representations reflect the value that society assigns to specific groups. Inequality in representation, therefore, constitutes an explicit statement of inequality in value. If our records of history, culture, and society are disproportionately associated with whiteness and maleness, then the human potential of females, males of color, and non-binary individuals is devalued relative to the privileged group. In a broad range of cultural products, from news media and history books to children's books, people who do not belong to the culturally dominant group are typically absent or portrayed through negative stereotypes (O'Kelly, 1974; Stewig and Knipfel, 1975; Dobrow and Gidney, 1998; Balter, 1999; Witt, 2000; Brooks and Hébert, 2006; Martin, 2008; Paceley and Flynn, 2012; Daniels, Layh and Porzelius, 2016).

While there exist myriad structural barriers to racial and gender equality woven throughout the organizations, laws, and customs of our society (Darity and Mason, 1998; O'Flaherty, 2015; Blau and Kahn, 2017; Muhammad, 2019; Chetty et al., 2020), inequality of representation is a key contributor to inequality in outcomes if it instills the belief that members of the underrepresented group are inherently deficient. Research from different disciplines supports the notion that representation gaps may be linked to socioeconomic inequality. For example, the experience of cultural subjugation may reduce the "capacity to aspire" (Appadurai, 2004). The absence of identity-specific positive examples of success can lead to a distorted view of the path from present action to future outcomes (Wilson, 2012; Genicot and Ray, 2017; Eble and Hu, 2020). This potential recursive loop from the self-image formed by the educational experience to socioeconomic success underscores the importance of addressing inequality in representation within educational materials.

Inequality in representation in the context of schools is particularly pernicious because educational materials are explicitly intended to shape students' views of the world around them, and schools make important contributions to the formation of children's social preferences (Cappelen et al., 2020). Importantly, the messages in these materials shape how children view *others* of different identities. When children do or do not see others represented, their conscious or unconscious perceptions of their own potential and that of unrepresented groups can be molded in detrimental ways and can erroneously shape subconscious defaults.

Empirical evidence suggests that the reverse also may be true: improving representation may improve outcomes. Closing the representation gap by revealing previously invisible opportunities may influence beliefs, actions, and educational outcomes for females and, separately, people of underrepresented racial and ethnic identities (of all genders) (Dee, 2004; Stout et al., 2011; Beaman et al., 2012; Riley, 2017). While not a panacea, such "subject-object identity match" (e.g., teacher-student identity match, or content-reader identity match) can help reduce academic performance gaps among multiple marginalized groups via a wide range of potential channels.[6]

I.B The Need for Better Measurement Tools

Systematically addressing these issues requires a systematic method for assessing the representations contained in the content used to instruct children. Educators and curriculum developers have worked to address this representation gap by, for instance, expanding the

[6]These include, but are not limited to: by reducing stereotype threat (Steele and Aronson, 1995); by potentially increasing the perceived likelihood of different possible futures for the individual (Wilson, 2012); and by expanding the perceptions and assumptions of those in majority-represented groups who thereby may be less likely to limit access to opportunities.

curriculum to include individual books that elevate the presence of an identity group. These efforts, however, are inherently piecemeal. Furthermore, the incidence, levels, and impacts of such efforts are likely to vary dramatically across teachers and schools, and the sheer quantity of content that they have to review or create is too large for any individual to manually track and assess. As a result, educators, administrators, and policymakers currently lack feasible ways to systematically identify such inclusive materials.

Children's books represent a prime opportunity to "fix the institution" by increasing equity in representation, particularly in books that highlight the diverse roles that people can perform in an equal society. Identifying such books has been done through content analysis, which historically has been conducted primarily by humans reading carefully through text, images, or other media while coding the presence of certain words, themes, or concepts by hand (Neuendorf, 2016; Krippendorff, 2018). Because this manual process is time-consuming and therefore costly, resource constraints have limited the scope of such work.

In this paper, we demonstrate how tools from computer vision and natural language processing can be used to systematically analyze content. We expand and develop tools for image analysis, pairing them with tools from text analysis used in recent work by Caliskan, Bryson and Narayanan (2017), Garg et al. (2018), and Kozlowski, Taddy and Evans (2019). These tools can facilitate broader and more cost-effective measurements of racial constructs, gender identity, and age in images and text in a larger set of content than could be analyzed by any one individual or institution.

There are challenges to this type of numeric measurement of representation, however. For example, racial constructs are multi-faceted and often ill-defined. To address this challenge, we measure different facets of the broad concept of race in various ways: skin color, putative race (that is, assigned by society), and birthplace.[7] It is important to focus on these racial constructs, because each of these concepts has been used in systems that perpetrate oppression and inequality by asserting a system of intrinsic hierarchy. In systems of explicit and implicit racism, European facial features are privileged over non-European features, such as those seen as African, Asian, or Indigenous peoples (MacMaster, 2001). In colorism, lighter skin tones are similarly either more desired or more associated with desirable traits, relative to darker skin tones (Hunter, 2007; Ghavami, Katsiaficas and Rogers, 2016). Separately, current methods measure gender identity in a binary way and neglect

[7]A wide range of research studies highlight the importance of both place of birth (Jencks and Mayer, 1990; Brooks-Gunn et al., 1993; Cutler and Glaeser, 1997; Leventhal and Brooks-Gunn, 2000; Sampson, Morenoff and Gannon-Rowley, 2002; Chetty, Hendren and Katz, 2016) and the color of one's skin (Banks, 1999; Hunter, 2007; Burton et al., 2010; Ghavami, Katsiaficas and Rogers, 2016; Keith and Monroe, 2016; Dixon and Telles, 2017) in determining one's chances of economic and social mobility

non-binary and gender fluid identities. While the methods we use are unable to address this shortcoming, it is an important venue for future work.

Furthermore, even numeric characterization of the representation of race and gender can be difficult and, if executed improperly, a tool for the perpetuation of bias. Because AI tools are designed by humans, they contain human biases (Das, Dantcheva and Bremond, 2018), and, if used improperly, their use can even perpetuate inequality (Fu, He and Hou, 2014; Nagpal et al., 2019; Krishnan, Almadan and Rattani, 2020). New scholarship shows, however, that careful attention to identifying and addressing these biases allows scholars and practitioners to overcome them while preserving the advantages of this type of computer measurement (Buolamwini and Gebru, 2018; Mitchell et al., 2019).

An important contribution of this paper is to explore how and whether intersectionality is addressed over time in books that are intentionally selected to highlight specific marginalized groups compared to books not selected to highlight any particular identity. Different aspects of identity, such as race, gender identity, class, sexual orientation, and disability, do not exist separately from each other, but rather are inextricably linked (Crenshaw, 1989, 1990; Ghavami, Katsiaficas and Rogers, 2016). The notion of "intersectionality" refers to the unique experiences of people whose identities lie at one or multiple intersections of these identities. It highlights the fact that such identities cannot simply be characterized by the sum of their parts; for example, the experiences of Black women cannot merely be summarized by a description of the experiences of all women and, separately, the experiences of all Black people.

Inattention to intersectionality can lead to the omission of groups with intersectional experiences. An effort by publishers to diversify by gender, for example, is likely to overrepresent the experiences of White women relative to women of color, given the relative abundance of White women in popular media. Even those who select content with an eye towards increasing representation of particular groups are themselves often products of an education system that reflects the structural racism, sexism, and other drivers of systematic inequality. Thus, even deliberate efforts to address inequality in representation may inadvertently perpetuate other inequalities, thereby contributing to the underrepresentation – or exclusion – of intersectional experiences.

II Data

School libraries serve as major purveyors of sanctioned visual content for children. The books they offer are accompanied by an implicit state-sanctioned stamp-of-approval. These books are generally targeted towards specific age groups, ranging from picture books

to print-only books. They are deliberately chosen and curated by librarians and school administrators, and are often selected because they transmit clear narratives about appropriate conduct, an account of important historical moments, or other, often identity-specific messages. For the purposes of our analysis, children's books also serve as a useful test case for image analysis tool development because they contain both illustrations and photographs. By drawing from a set of materials that has a broad range of image types, we are able to develop more flexible face detection and feature classification models that can recognize a diverse set of images.

II.A Award-winning Children's Books

Our data come from a set of children's books considered to be of high literary value and likely to be found in US schools and libraries. We use books that received awards administered or featured by the Association for Library Service to Children (ALSC), a division of the American Library Association (ALA). Our sample comprises 1,130 books, and each book in this sample is associated with one of 19 different awards.[8]

We divide these award-winning corpora into two primary "collections" of books, which we call the "Mainstream" and "Diversity" collections. Figure 1a presents the full list of awards in our sample and the collection(s) into which we categorized them. Figure 1b and Table 1 show the sample size of each collection by decade.

Mainstream Collection. The Mainstream collection comprises books that have received either Newbery Honors or Caldecott Honors, the two oldest children's book awards in the United States. The Newbery Medal, which was first awarded in 1922, is given to authors of books that are considered to be the "most distinguished contribution to American literature for children." The Caldecott Medal, which was first awarded in 1938, is given to illustrators of "the most distinguished American picture books for children." These books are explicitly chosen for their literary quality and not their popular appeal per se. Books receiving these awards are considered to be of general interest to all children and are quickly incorporated into mainstream outlets for children, such as school libraries (ALSC, 2007; Koss, Johnson and Martinez, 2018). The covers of these books are often marked by a conspicuous picture of the award. The primary goal for studying these books is to understand the representation of race, gender, and age in a set of books to which a large proportion of American children are exposed.

[8]The 19 award corpora are comprised of 3,447 total books which either won an award or received an honorable mention; we obtained and digitized 1,130 of these books using both library and online resources.

Diversity Collection. The Diversity collection is a set of books featured by the ALSC that purposefully highlight the representation of excluded or marginalized identities.[9] These books are also likely to be placed on "diversity lists" during events such as Black History Month or Women's History Month. Two goals of studying representation in these books are one, to measure the efficacy of these books in highlighting the identity on which they focus, and two, to measure the levels of representation of identities beyond the identity on which a given award focuses, particularly to assess the extent to which they account for intersectional experiences.

This collection includes books that have received the following awards: American Indian Youth Literature Award, Américas Award, Arab American Book Award, Asian/Pacific American Award for Literature, Carter G. Woodson Book Award, Coretta Scott King Book Award, Dolly Gray Award, Ezra Jack Keats Book Award, Middle East Book Award, Notable Books for a Global Society, Pura Belpré Award, Rise Feminist Award,[10] Schneider Family Book Award, Skipping Stones Honor Award, South Asia Book Award, Stonewall Book Award, and Tomás Rivera Mexican American Award. The first of these awards was the Coretta Scott King Award created in 1970 specifically to highlight African American writers, partly because no such writer had received either the Newbery or Caldecott Medals as of that point. Other awards were created more recently, such as the South Asia Book Awards in 2012.

We also create smaller collections of these awards that highlight the following specific identity areas: people of color, African American people, females, people with disabilities, and lesbian, gay, bisexual, transgender, and queer (LGBTQ) people.

While different awards begin in different years, we do not limit the analysis to years in which all awards have books in the sample. The use of books persists over time, and it may be just as likely, if not more likely, for someone to select a book considered to be a "classic" (typically an older book) rather than to select a book more recently published.

We present summary statistics of the books in our sample, by collection, in Table 1. This shows key information about each collection, such as the number of years each award within a given collection has been in existence, as well as aggregate information about each collection, including the average length of the books (number of pages, number of words contained) and summaries of the measurements we describe in the following sections.

[9] We selected children's book awards featured on the ALSC website, many of which are administered by different organizations.

[10] The Rise Feminist Award was formerly known as the Amelia Bloomer Award.

II.B Why Focus on Award-winning Books?

Scholars of children's literature assert that receiving an award from the ALSC, and particularly one of the Mainstream awards, places the book into the "canon" of children's literature and makes it a common feature in homes and school libraries (Smith, 2013; Koss and Paciga, 2020). Furthermore, the winners of the broader set of awards are commonly featured in numerous venues that are part of children's learning experience, from book fairs and catalogues to school curricula and summer reading lists (Knowles, Knowles and Smith, 1997).[11]

We use publicly available, book-level, daily checkout data from the Seattle Public Library system from 2004 to 2017 to show empirical evidence of the relationship between receipt of these awards and book popularity. Most of these awards are presented annually, and many award recipients are announced at the ALA's Midwinter Meeting, which typically occurs near the end of January. To be eligible for these awards, a book must be published in January of that year or any time in the prior year. In Figure 2, we present an event study that shows the average number of daily checkouts per book by collection, centered around the time when awards are announced.[12] We plot checkout rates for three sets of books in the library's collections: (1) all books winning Mainstream awards in that year; (2) all books winning Diversity awards in that year; and (3) a random sample of 10 percent of the children's books that did not win one of the awards in our sample that were published either in the year prior to the award or in the same year as the award, prior to February 1st in that year.[13]

We see that checkout rates of books selected for Mainstream awards increase around the time of the announcement of awards, surpassing the average daily checkouts of other books.[14] This persists for at least two years after the award announcement, during which average daily checkouts of the Mainstream collection plateau at a rate roughly twice that of the comparator groups – books from the Diversity collection and books that did not win an award from our sample. Checkout rates of books in the Diversity collection group do

[11]Our time window for the inclusion of books in our sample ranges from the inception of the award to the present. We do not limit the time frame to the same set of years for all awards, because the use of these award-winning books often persists for decades after their receipt of the award. For example, picture books such as *The Snowy Day* by Ezra Jack Keats (1962) and novels such as *Charlotte's Web* by E.B. White (1952) came into the collection before 1970, when the first Diversity collection book entered the sample, yet they remain an important part of children's literature options even today.

[12]We describe the empirical specification and data cleaning details in the Data Appendix.

[13]These are books that did not receive one of the awards in our study, but they may have received recognition from a different source. For brevity, we refer to this third set of books as "non-winners" or "non-award winners."

[14]The three series exhibit parallel trends during the year prior to the award announcements.

not increase similarly to those of books in the Mainstream collection, though their average daily checkout rates trend upwards over the threshold, while those of the non-winners trend downwards. Overall, this suggests that Newbery and Caldecott award winners have greater influence than other children's books, and children may be more likely to be exposed to the messages in books recognized by Newbery and Caldecott than other books, consistent with previous qualitative assessments of these books' central role in children's literature (Smith, 2013; Koss and Paciga, 2020). This is also reflected in analysis of book sales data from publishers, who see large gains in sales – of similar or even larger magnitudes – after a book receives an award (Cockcroft, 2018).

II.C The Need for Computer-driven Content Analysis

Analysis of these features in books has historically been the domain of the field of content analysis. Conventional content analysis is performed by human coders, or "by hand" (Neuendorf, 2016; Krippendorff, 2018). The 1,130 books in the sample contain 162,872 pages of content and 54,043 detected faces. It would be cost-prohibitive to analyze this much content through manual content analysis techniques, let alone to analyze the much larger bodies of potential content that practitioners or policymakers regularly consider for inclusion in curricula. As outlined in Section VIII, a back-of-the-envelope calculation suggests that it would cost between $245,000 and $325,000 to analyze all the pages in our sample using traditional content analysis methods.[15]

To mitigate these costs and to more systematically analyze representation in the large volume of images and text these book pages contain, we extract measures of representation using automated methods, which we describe in Sections III and IV.

III Images as Data

In this section, we describe our development and application of software tools to measure the content of images. The maxim "a picture is worth a thousand words" speaks to the fact that an image often contains a wide range of messages. Perhaps the most direct form of representation is what a child sees in the visual portrayals of people in the images shown in a book, particularly before a child becomes textually literate. Despite this, images are not widely used as a source of data in the social sciences. This is in stark contrast to the use of text as data, which has seen substantial attention in the past decade (Gentzkow and Shapiro, 2010; Gentzkow, Shapiro and Taddy, 2019; Kozlowski, Taddy and Evans, 2019). A main contribution of this paper is to address this gap by introducing, applying, and

[15]The marginal cost of analyzing each additional page using traditional content analysis methods is a linear function of the per-page cost; whereas the marginal cost of analyzing each additional page using developed artificial intelligence tools is relatively trivial.

developing tools for the computer-led analysis of the content of images.

Perhaps the first message people take from an image is that of representation: namely, *who* is contained in an image. The tools that we develop and apply in this paper identify faces of characters contained in images – both photographs and illustrations – and classify their skin color, race, gender, and age. In this section, we will describe the component processes: identifying characters' faces, then identifying the color of the skin, and, separately, classifying their race, gender, and age. We depict this process in Figure 3a and refer to it as our "Image-to-Data Pipeline."

III.A Face Detection

Our first step in converting images to data is to use computer vision tools to identify the faces of characters in each image.[16] Specifically, we trained a custom transfer learning model to detect and classify images on a scanned book page, using Google's AutoML Vision (Zoph and Le, 2017).[17] Transfer learning is a process which facilitates the use of a pre-trained model as a "shortcut" to learn patterns from data on which it was not originally trained. AutoML is an artificial-intelligence-based technology for conducting "automated machine learning." Using a series of labeled data sets, we train models that recognize and identify patterns in images to detect faces and classify features of interest. The AutoML tool algorithmically optimizes its performance of classifying features via fine-tuning its neural networks.[18]

Classifying the identity of people represented in images is a complex problem because of the wide variance in the way people can be represented. This problem is further complicated in the context of children's books by the substantial variation in the characteristics of the images in these books. First, the images in these books consist of both illustrations and photographs. This is notable, in particular, because most existing models were trained exclusively on photographs, leading these models to undercount illustrations.[19] Second, these images are also likely to show both human and non-human characters. These characters could have human skin colors (e.g., different shades of beige and brown), non-typical skin

[16]Computer vision involves teaching a computer to view and interpret images as a human would. Face detection is a subset of computer vision, in addition to identifying features such as colors, objects, and emotions.

[17]A neural network is a program designed to model the way the human brain functions, wherein the computing system is given examples and learns to perform tasks by analyzing them, usually without being given explicit instructions.

[18]More specifically, AutoML seeks the optimal network architecture and hyper-parameter configuration which minimizes the loss function of a model. Google's AutoML Vision is based on neural architecture search and transfer learning technologies.

[19]This concern is amplified by the large proportion of illustrations in our data: in a random sample of manually labeled images, we found that over 80 percent were illustrated, as opposed to photographic.

colors (e.g., blue or green), or monochromatic skin colors (e.g., greyscale or sepia). Finally, characters could be shown in different poses, such as facing the viewer, shown in profile, or facing away from the viewer.

To address the potential undercounting of characters in illustrations, we trained a transfer learning face detection model (FDAI) using a manually-labeled data set of 5,403 illustrated faces drawn from two sets of books that contain a wide variety of illustrated characters.[20] To train the model, we split the data set into training (80 percent of the data), validation (10 percent of the data, used for hyper-parameter tuning), and test (10 percent of the data, used for evaluating the model).[21]

The test data are manually labeled data that are kept separate from the training and hyper-parameter tuning algorithms.[22] The models compare results from the algorithms to the manual labels in the test data to evaluate the accuracy of the algorithms. This process provides two specific parameters that are commonly used to evaluate the performance of this class of model: "precision" and "recall."[23] 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, tells us 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 proportion of the number of correctly detected faces out of the actual number of faces in the book.[24] Formally:

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

[20]We used books in the Newbery and Caldecott corpora. A face was manually labeled if it could be easily observed. If a face was not detectable by a human, then we assumed it would not be easily detected by a machine. There were on average three detectable faces in each labeled image. We refer to our face detection model as FDAI (face detection using AutoML trained on illustrations).

[21]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 dataset), 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.

[22]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 dataset.

[23]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.

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

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

The higher the precision, the fewer false positives the model produces. In other words, precision tells us from all the test examples that were predicted with a certain label, which ones are truly of that label? On the other hand, the higher the recall, 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 76.8 percent recall. In other words, 6.6 percent of the faces we identify may not, in truth, be faces (a false positive), while the model may neglect to identify one in 4.5 "true" faces (a false negative).

III.B Image Feature Classification: Skin Color

Skin color is an important and distinct dimension of how humans categorize each other. Skin color is likely to be an immediate feature of an image that a viewer is likely to process. Distinct from putative race, skin color is itself a site of historical and ongoing discrimination with clear impacts on health and in the labor market (Hersch, 2008; Monk Jr, 2015). From a measurement perspective, it is a parameter for which we can more clearly observe the "ground truth," as the color detected by the computer is a value purely based off of each pixel value, as compared with the categorization of putative race, which may vary by observer. In this subsection, we introduce and describe our method for measuring the skin color of the character faces our model detects.

We develop a novel method to classify the skin color of these characters. Our skin color classification method involves a three-step process: (1) "segmenting" the skin on the face (isolating the parts of the face which contain skin from other facial features), (2) extracting the dominant colors in the identified skin, and (3) constructing measures of the skin color of each face using the dominant colors identified. Figure 3a illustrates this process.

III.B.1 Skin Segmentation: Fully-Convolutional Conditional Random Field

We first isolate skin components of the character's face using convolutional neural networks (CNN).[25] 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

[25] A convolutional neural network (CNN) is a multilayer, fully connected neural network, often used for machine-led image analysis.

into account skin color (in)consistency across variations in illumination, acquisition types, ethnicity, geometric transformations, and partial occlusions (Lumini and Nanni, 2020). To deal with these issues, we isolate skin from non-skin parts of the detected face using a deep learning approach called Fully-Connected Convolutional Neural Network Continuous Conditional Random Field (FC-CNN CRF).[26]

This skin segmentation method (FC-CNN CRF) comprises three steps. First, we apply a fully-convolutional neural network (FC-CNN),[27] which is a type of convolutional neural network (CNN) where the last fully-connected layer is substituted with a convolutional layer that can capture locations of the predicted labels. This allows us to predict periphery landmarks such as the edges of the facial skin area, eyes, nose, and mouth. Second, we then use these predicted landmarks to extract a "mask" for the targeted facial region using the convex hull function in SciPy's Python library. Third, we refine this mask by applying a continuous conditional random field (CRF) module, which predicts the labels of neighboring pixels (i.e., whether they are predicted to be skin or not skin) to produce a more fine-grained segmentation result.[28] The resulting mask provides the segmented skin that we can then use to classify skin color. In Figure 3a, we illustrate the process of detecting a face and then isolating the facial area of interest through skin segmentation.

III.B.2 Skin Color Classification: *k*-means clustering

We then identify the predominant colors in the pixels of the face mask created in Section III.B.1 using k-means clustering. k-means clustering is a traditional unsupervised machine learning algorithm whose goal is to group data containing similar features into k clusters.[29] Specifically, k-means clustering partitions all the pixels in the "segmented" skin into k clusters, each pixel being assigned to the cluster with the nearest mean.[30] For our analysis, we partition the pixels into five clusters (i.e., where k takes a value of five) and we drop the pixels in the smallest two clusters as they tend to represent to shadows, highlights, or non-skin portions of the detected face.

[26]Specifically, we use a Convolutional Neural Network (CNN) cascade which parses the skin from the detected face via a fully-convolutional continuous Conditional Random Field (CRF) neural network (Zhou, Liu and He, 2017). To do so, we used the trained model proposed in Jackson, Valstar and Tzimiropoulos (2016) to automatically conduct semantic segmentation of the facial skin in which we adapt code from Lu (2018) for parsing skin and from Beyer (2018) for CRF post-processing.

[27]An equivalent term for this is Fully-Convolutional Continuous Conditional Random Field. "Fully-Convolutional" implies fully-connected CNN in this case.

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

[29]Clustering entails partitioning data points into a small group of clusters.

[30]We used the k-means clustering function implemented in the the scikit-learn Python library Sculley (2010). Originally from the field of signal processing, k-means clustering is a tool used in various applications that require the grouping of fields of data into disparate clusters.

Next, we take the centroid of each of the remaining three largest clusters and we use a linear mapping to convert these three values from RGB space, the color space used in the k-means clustering output, into the L*a*b* color space.[31] L*a*b* is a perceptually uniform space that expresses color as three values: L*, which we refer to as "perceptual tint," and a* and b* for the four unique colors of human vision: red, green, blue, and yellow.[32] This conversion allows us to reduce the dimensionality of the variable to a single value and interpret a given numerical change in the color values as a similar perceived change in color.

After this conversion, we take the weighted average of the centroids of the largest three clusters; weights correspond to the relative number of pixels assigned to each cluster. We use this weighted average to represent a face's representative skin color. By separately identifying the centroids of the largest three clusters and taking their weighted average, we can more accurately classify the actual skin color depicted and minimize misclassification due to irregularities or idiosyncrasies in the image, for example, from the presence of shadows or hair that the skin segmentation process failed to remove.

III.B.3 Skin Color Classification: Perceptual Tint

After collapsing the centroids of the largest three clusters to their weighted average, we separate them into three categories of skin color type: (1) monochromatic skin colors (e.g., greyscale, 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:

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

Where μ_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 predicted labels using the equation above for every integer value of T between zero

[31] L*a*b* is also known as CIELAB.

[32] A more common term for L* is "perceptual lightness," but to decenter and de-emphasize "lightness" or "brightness" relative to "darkness," we refer to the concept as "perceptual tint," or "tint."

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 $T = 13$; 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 tones (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.[33] Otherwise, it is classified as a polychromatic non-typical skin color.

$$Human_i = [1 - Monochromatic_i] \times \mathbb{1}[R \geq G \geq B] \tag{2}$$

$$NonTypical_i = [1 - Monochromatic_i] \times [1 - Human_i] \tag{3}$$

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. We use this continuous measure of perceptual tint along with the skin color tercile classifications (darker, medium, or lighter) as our measures for skin color.

III.C Image Feature Classification: Race, Gender, and Age

In this section, we discuss how we classify putative race, gender, and age of detected faces in images. We build a method for the analysis of race, gender, and age by training a multi-label classification model using Google's AutoML Vision platform. Due to the large amount of manually labeled data necessary to train these deep learning models and due to

[33]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).

the fact that there are no public data sets using illustrations, we use transfer learning to predict gender and age for both photographs and illustrations in our children's books using a model trained on photographs. Therefore, to train this model, we used the UTKFace public data set (Zhang and Qi, 2017), which contains over 20,000 photographs of faces with manually verified race, gender, and age labels.[34] We split the data set into three parts: training (80 percent of the data), validation (10 percent of the data), and test (10 percent of the data). The resulting model has 90.6 percent precision and 88.98 percent recall. In other words, 9.4 percent of the images assigned a given race, gender, or age label will, in truth, not possess that trait (a false positive), while 11 percent of the images not assigned the label for that trait would, in truth, possess it (a false negative). The main drawback of this model is that it was trained on photographs while the majority of the faces in our children's books are illustrations.[35]

Race Classification (Images). The model assigns the probability that a detected face is of a given race category: Asian, Black, Latinx + Others, White.[36] Each identified face is assigned to the race category to which the model assigns the highest predicted probability.[37,38]

Gender Classification (Images). For each face detected, we predict the probability that the face is female- (or male-) presenting. We also 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.[39]

We recognize that these classifications are imperfect and focus only on the performa-

[34]The labels in the data set include: Gender (male or female), Age (infant (0-3), child (4-11), teenager (12-19), adult (20-64), senior (65+)), Race (Asian (a combination of Asian and Indian), Black, White, and others (e.g., Latinx, Middle Eastern).

[35]In a random sample, 84.2 percent of the detected faces were illustrations. Future work would include the creation and usage of a manually labeled dataset of illustrated faces to use as training data to more precisely predict the race, gender, and age of faces detected in illustrations.

[36]The race labels in the original model were defined in the UTKFace dataset 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.

[37]Previously, many existing artificial intelligence models that classified putative race had a high error rate, both misclassifying the putative race of identified people and, in "one-shot" models that identify existence of people and their putative race simultaneously, misclassifying people as non-human (Fu, He and Hou, 2014; Nagpal et al., 2019; Krishnan, Almadan and Rattani, 2020). Much work has been done to acknowledge and address these disparities (Buolamwini and Gebru, 2018; Mitchell et al., 2019)

[38]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.)

[39]We compare these predictions to a manually labeled random sample of 2,836 detected faces and present the results in the Data Appendix.

tive 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 child if the probability assigned to the age categories comprising the larger child bin is larger than 50 percent, and as adult otherwise.[40]

IV Text as Data

In this section, we describe the tools we use to measure representation in the text of books. Social scientists have manually analyzed the messages contained in text of printed material for centuries, which is labor- and time-intensive (Neuendorf, 2016; Krippendorff, 2018). Recent work by economists and sociologists showcases how the computational speed and power of (super)computers can be harnessed to conduct automated text analysis, greatly accelerating work traditionally done by hand (Gentzkow, Kelly and Taddy, 2019; Kozlowski, Taddy and Evans, 2019). We draw from this work and, in particular, a series of natural language processing tools that take bodies of text – e.g., from a book – and extract various features of interest. In Figure 3b, we show our process of extracting text from digitized books and then analyzing it; we refer to this as our "Text-to-Data Pipeline."

The first step in conducting this analysis is to extract text from digital scans of books by using Google Vision Optical Character Recognition (GVOCR). We input the raw files into GVOCR, which then separately identifies text and images (e.g., illustrations and photographs) in each file. 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.[41]

[40] We compare these predictions to the same manually labeled random sample of 2,836 detected faces used for comparison in the gender classification exercise and present the results in the Data Appendix.

[41] 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

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. 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. – for example, "MLK" – become "Martin Luther King Junior").

From these text data, we then derive several features. These features include: token (single word) counts, the presence of famous people, and the first names of characters. In the rest of this section, we describe how we use these features to construct measures of the representation of gender, race, and age in the text of each book.

IV.A Text Analysis: Token Counts

One branch of traditional content analysis consists of enumerating words that represent a particular attribute (Krippendorff, 2018). This process generates counts of different "tokens," which comprise a maximal sequence of non-delimiting consecutive characters. In our context, a token is an individual word. We generated a set of tokens associated with identities related to gender, race, or age. The vocabulary used for each of these lists is available in the Data Appendix.[42] We aggregate counts of these words by their respective identity category (such as female or male) by book, generating our "token count" measures of the representation of each identity in each book (Neuendorf, 2016).

Gender (Token Counts). To calculate gender representation in token counts, we calculate the proportion of words with a gendered meaning that refers to females. For our main analysis, we combine specific gendered tokens (e.g., queen, husband, daughter) with gendered pronouns (e.g., her, he, she).[43,44,45]

We show how gender representation varies on three additional dimensions: one, whether the gendered identity is represented by individuals (singular) or groups (plural); two, whether the character is placed as the subject or object of a sentence; and three, by the

performance relative to manual coding also showed GVOCR performed the best.

[42]We use the spaCy library to generate these counts, but we see similar patterns in our findings when we use NLTK instead.

[43]Traditional content analysis often restricts gendered words to pronoun counts. We show the sensitivity of our findings related to this construct by restricting the analysis to gendered pronouns only in Appendix Figure A12. Our results are robust to this alternate specification.

[44]We calculate the total number of words in a book by removing all punctuation from the text and then dividing the text into a list of words using either the "nlp" package in the spaCy library or the "word_tokenize" package in the NLTK library. The length of this list provides the total number of words in a given text.

[45]In some cases, characters have a gendered title such as "Señora Cuervo," "Uncle Robin," or "Queen Swan." We count these gendered titles in the specific gendered token counts.

age of the gendered word. To analyze singular and plural representation separately, we separate gendered tokens into those referring to singular cases (e.g., daughter) and plural cases (e.g., daughters). To analyze whether the character is the subject or object of a sentence, we generate counts of the number of gendered pronouns that are capitalized versus lowercase, under the theory that an individual who is the subject of a sentence is in a position of more active importance than the same character when used as the object and thus occupying a more passive role. To analyze representation of gender by age, we generate a list of "younger" gendered words (e.g., princess, boy) and "older" gendered words (e.g., queen, man).

Nationality (Token Counts). To calculate nationality representation in token counts, we calculate the proportion of all words that refer to nationalities (e.g., Mexican, Canadian).

Color (Token Counts). As another proxy for the analysis of race, we calculate the proportion of all words that refer to colors (e.g., black, white, blue).

IV.B Text Analysis: Named Entity Recognition

We also measure the representation of gender and race among named characters in these stories, be they fictional or historical. A series of studies show that exposure to salient examples of historical figures or celebrities from historically marginalized identities can lead to meaningful change in social attitudes towards people who hold that identity, as well as an increase in beliefs and academic performance among children who share that identity (Marx, Ko and Friedman, 2009; Plant et al., 2009; Alrababah et al., Forthcoming). To do so, we use a tool called Named Entity Recognition (NER).[46] NER identifies and segments "named entities," or proper nouns, starting with a pre-defined library of such entities and also identifying new entities through the application of neural nets. NER recognizes these entities in strings of text; applying NER to our data, we identify these entities and count how many times each specific named entity is mentioned in a given book. We then associate these frequency counts with identifiable traits of the people identified by NER, such as their race, gender, or place of birth. There are two types of named entities that we identify: (1) famous characters and (2) first names of characters.

IV.B.1 Famous People

To identify the instances of famous characters represented in books, such as Martin Luther King Junior or Amelia Earhart, we match all of the entities identified by NER that

[46]We run our NER analysis using the open-source software library spaCy, which employs convolutional neural networks for both text categorization and NER. Another commonly-used library for NER is NLTK, but it only recognizes single words for NER, whereas spaCy can recognize strings of words as a distinct entity. For example, "Martin Luther King" would be recognized as one entity in SpaCy but as three entities with NLTK ("Martin," "Luther," and "King").

have at least two names (for example, a first and last name) with a pre-existing data set, Pantheon 2.0, that contains data from over 70,000 Wikipedia biographies which have a presence in more than 15 language editions of Wikipedia (Yu et al., 2016). This generates a data set of 2,697 famous people. We count the number of unique books in which each famous person is mentioned as well as the number of times they are mentioned in each book.[47]

Gender and Birthplace (Famous People). The Pantheon 2.0 data set contains information on the gender and birthplace of these famous people. We match these data to each famous figure identified from the NER in our data.[48]

Race (Famous People). We then manually code race for each identified person. This was conducted based on a manual internet search for each person, starting with Wikipedia.[49] 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, they were then classified as multiracial.

IV.B.2 Character First Names

We also study the representation of gender among people who are named but not identified as "famous" using the methods described above. Using the named entities identified by the spaCy NER engine, we limit the sample to those entities categorized as a person and remove the famous characters we found by applying the process described in Section IV.B.1.[50] We then categorize the remaining named entities and construct a data set containing the name of each unique character and the number of times that character is mentioned in a given book.

Gender (Character First Names). To identify the gender of characters not identified as famous, we extract the first name of each remaining named entity and estimate the

[47]Since NER tools are not perfect, the longer an entity's name the more likely it is that only part of the name is identified. It is important to note that we have observed several instances where Martin Luther King Junior was mentioned in our text but only the first part of his name was recognized and saved as "Martin Luther." As a result, we under count the number of times Martin Luther King Jr. is mentioned and over count the number of times Martin Luther is mentioned. This is a limitation of our method.

[48]The Pantheon 2.0 curators run a classifier over the English text of the Wikipedia biographies to extract information such as place of birth and gender from each biography. Their classifier was trained on a data set called Pantheon 1.0 (Yu et al., 2016) which contains a subset of manually curated biographies.

[49]Note that coding of putative race is subject to the individual biases and perceptions of each human coder and may be classified with error.

[50]NER tags each entity with a different category: people, locations, currency, and more. This entity categorization (e.g., person, location) is not always correct, so there may be entities misclassified or missed overall. We do not use this categorization when identifying famous characters.

probability that the character is female using data on the frequency of names by gender in the US population from the Social Security Administration. For example, if a character's first name is "Cameron," our estimated probability that the character is female is 9.16 percent because that is the proportion of people named "Cameron" in relevant Social Security data who are female. 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. Using this method, we are able to make gender predictions for approximately 61,430 characters. 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 96.35 percent accurate.[51]

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.[52]

IV.C Text Analysis: All Gendered Mentions

We aggregate all gendered mentions (gendered tokens, predicted gender of character first names, and matched gender of famous characters) to generate a composite measure of gender representation in text.

V Measures of Representation Used in the Analysis

To generate the estimates of representation we present – either at the collection or collection by decade level – we first collapse each variable to the book level, and then calculate the average across books in a given collection. For example, to find the average probability that a detected face in a book belonging to the Mainstream collection is female-presenting, we first find the average probability that a face is female-presenting over all the faces in each book in the collection and then take the average across books. This approach ensures that our measures of race, gender, and age representation in each book are equally weighted. In other words, books with more faces do not receive more weight in the collection averages than books with fewer images. We describe these measures below and in Table 2.

[51] We do not classify race using first names only. Other recent text analysis has shown that conventional methods for classifying race of names fail to successfully distinguish between Black people and White people (Garg et al., 2018).

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

V.A Variables of Analysis

In this section, we describe the ways in which we measure racial constructs, gender identity, and age in images and text.

Race Representation. We measure racial constructs through: (1) skin color classification of detected character faces, (2) race classification of detected character faces, (3) manually coded race of famous figures, (4) birthplace of famous characters, and (5) counts of words relating to nationalities and, separately, color word token counts.

Gender Representation. We measure representation of gender identity through: (1) gendered pronoun counts, (2) gendered token counts, (3) gender classifications of famous characters, (4) predicted gender of characters based on their first name, and (5) predicted gender of detected character faces.

Age Representation. We measure representation of age through: (1) age-by-gender word counts and (2) predicted age of detected character faces.

V.B Comparator Data

To explore whether the trends in representation track the US population share of people of different identities, we draw from US census data, which provides population shares by race, gender, and age (Gibson and Jung, 2002). In census data, Latinx is 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. Similarly census data on the number of people who identify as "Multiracial" or "Other" are not available for all years in our sample.

V.C Presenting our Results

We present results summarizing our measurements in the following ways:

Proportion of entities with a given trait. For categorical variables, we primarily use bar charts to show book-level proportions, averaged within a collection, for different measures of representation. For example, using our image data, we show the proportion of female faces within a book, averaged across books within a collection; using our text data, we show the proportion of female gendered words within a book, averaged across books within a collection.

Distributions. For continuous variables, we show probability density plots of the proportion of the observations – be they the words or faces detected in a book – across books in each collection over the set of possible values of the variable. For example, we plot the

distribution of books which have a given proportion of gendered words that are female across the range of possible values (0%-100%). It is important to note that these are estimated densities and that the density plots do not convey information on sample size.

Patterns over time. We also plot how collection averages change over time, using line graphs to show the evolution of decade-specific estimates for these variables.

Comparing measures within collections over time. When we want to compare two different measures within the same collection in a given decade we use scatter plots. In these plots, each point represents the average over all books in a single collection within a given decade. The size of the point corresponds to the number of books in a given collection for a given decade and the color of the point corresponds to a given collection. This means that the Mainstream collection has ten data points because it spans ten decades, but the Female collection only has one data point because that collection begins in the 2010s and only spans one decade.

VI Results

In this section, we present our results characterizing the representation of race, gender, and age in the images and text of the books in our collections. First, we present patterns of the representation of racial constructs (skin color, race, and place of origin) across collections and time. We then present patterns of the representation of gender identity across collections and time. We conclude the section with a discussion of our results summarizing the representation of race, gender, and age in these books.

VI.A Representation of the Construct of Race

In this section, we show results for traits which characterize the latent, human-perceived construct of race in images and in text – skin color, putative race, and place of origin – as discussed in Sections I, III, and IV. Our measures include: (1) the representative skin color of detected character faces in images, (2) the predicted race of detected character faces in images, (3) classification of the putative race of famous figures named in the text, (4) the birthplace, or place of origin, of famous figures named in the text, and (5) token counts of color words.

Skin color of faces. We first report our estimates of the representation of race in images, focusing on the representative skin color of a character's face. In Figure 4, we show the representative skin colors of all the individual faces we detect in the images in the books in each collection. We show these by the three color "types" present in these images: polychromatic human skin colors,[53] monochromatic skin colors (e.g., black and white, sepia),

[53]Skin color is classified as "human" where the segmented skin's color is R $\geq$ G $\geq$ B, conditional on the

and non-typical skin colors (e.g., blue, green).[54] The y-axis indicates the standard deviation of the RGB values of each face. The higher the standard deviation, the more vibrant the color.[55]

In Figures 5 and 6, we show patterns in representation across collections overall and across collections over time. First, Figures 5a and 6a show the distribution of perceptual tint for detected faces in the Mainstream and Diversity Collections. These figures show that, regardless of image type, the faces in the Diversity Collection have darker average skin tones than those in the Mainstream. A Kolmogorov-Smirnov test rejects the equality of the two distributions ($p < 0.001$) which suggests that the skin color distributions between the two collections are statistically distinct. Furthermore, the distribution of skin color tint in the Mainstream collection also has a much smaller variance than that of the Diversity collection (a test of the null hypothesis that the two variances are equal rejects equality with $p < 0.001$). This implies that there is a greater variety of skin color tint shown in the Diversity collection.

We then examine the proportion of characters whose faces fall into one of three skin color terciles: darker, medium, or lighter. Figures 5b and 6b show that, over time, the proportion of characters who have skin colors in the medium and darker skin color terciles is increasing relative to those in the lighter skin color tercile, both for the Mainstream and Diversity Collections. Figures 5c and 6c show the distributions across these terciles, for all seven collections. For both Mainstream and Diversity Collections, the medium skin color tercile is the most represented, with almost half of all faces in both collections falling in this tercile. In the Mainstream Collection, however, lighter skin is in the second most common skin color tercile (roughly one third of faces), while in the Diversity Collection, darker skin comprises the second most common skin color tercile (roughly 40 percent of faces). This suggests that the Diversity collection is more representative of characters that have darker skin tones. Of the seven collections, the Mainstream Collection has the lowest proportion of faces falling in the darker skin color tercile and the Female Collection has the greatest proportion. 5a and 6a). Compared to the Mainstream collection, all other collections have greater representation in the medium and darker skin color terciles. This occurs both in collections recognized for highlighting the experiences of people of color – and especially

skin color not being classified as monochromatic.

[54]We show these for each collection by decade for human skin colors (Appendix Figure A1), monochromatic skin colors (Appendix Figure A2), and non-typical skin colors (Appendix Figure A3). We find that in the earlier decades of the Mainstream Collection, there was a greater proportion of monochromatic images, with a general trend over time to have more polychromatic images. In the Diversity Collection, and in particular the People of Color Collection, there is a consistently high proportion of monochromatic images, perhaps representing the use of historical black-and-white photographs.

[55]We found that when the standard deviation was below 13, the image was more likely to be a monochromatic picture.

those that highlight the experiences of Black people – as well as in those in the Female collection.[56]

Race of detected characters. We then examine the predicted race of characters in images. Figure 7 shows that the Mainstream collection is likely to show characters *within* a given race as lighter than their counterparts in the Diversity collection. We see in Figure 8 that detected character faces are overwhelmingly classified as being White males or females.[57]

Race of famous figures. To examine the race of the famous figures mentioned in the text, we count the number of famous people mentioned at least once in a 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 mentioned at least once in two separate books within the Diversity collection, we would count her twice for that collection. In Appendix Figure A9, we show the proportion of famous figures in each collection identified as Asian, Black, Indigenous, Latinx, Multiracial, or White. We find that, in all collections, the famous figures mentioned are predominantly White. In the Mainstream Collection, over 90 percent of famous figures are White.[58] The African American Collection is the only collection to have a majority identity other than White represented. Other groups appear far less frequently. Black people are the next-most represented, comprising 50 percent of the famous people in the African American collection, and 7 to 29 percent in the other collections. Famous people of Asian, Latinx, Indigenous and Multiracial identities account for between 3 and 10 percent of famous people *combined*, a high level of inequality in representation relative even to US population averages.[59]

We also examine how representation of race in famous figures varies by gender in Figure 9, which shows the proportion of famous figures in each race-by-gender category. We find that the majority of famous characters in almost all collections are White males. In the African American collection, there are more Black male famous characters by 0.6

[56]As we see in Appendix Figure A3, which shows these estimates for polychromatic "non-typical" skin colors, the method of classifying "human" vs. "non-typical" skin colors may underestimate the number of darker-skinned faces if the browns that are used do not follow the polychromatic R $\geq$ G $\geq$ B rule. However, Appendix Figure A4 shows that this does not change the patterns in skin color representation by collection over time.

[57]Appendix Figure A5 shows that most pictured characters are classified as being White. Appendix Figure A6 shows a substantial portion of pictured characters predicted to be female-presenting, and Figure 8 suggests that most of these pictured characters are White females. We map these shares on their respective shares of the US population in Appendix Figures A7a and A7b

[58]Recent work reporting conventional content analysis of the race of main characters in the Caldecott and, separately, Newbery award-winning books finds qualitatively similar results (Koss, Johnson and Martinez, 2018; Koss and Paciga, 2020).

[59]For example, the US Census Bureau estimates that only 60 percent of the US population is non-Latinx White (US Census, 2019).

percentage points. 37.4 percent of the famous characters are Black males, and 36.8 percent of the famous characters are White males. In all other collections, White males are 49.8 percent or more of all famous people mentioned. The next most represented groups are White females (9-25 percent of famous people) and Black males (5-37 percent of famous people). The representation of Black females (between 2 and 8 percent of famous people, except in the African American collection, where they comprise 13 percent) is consistently less than that of Black males, despite their roughly equal shares in the population. This highlights that even within collections of books curated to highlight a given racial identity, race and gender are often treated as mutually exclusive categories of experience, overlooking the representation of groups such as Black females whose identities lay at the intersection of multiple experiences of exclusion.

In Appendix Table A1, we list the five most frequently mentioned famous people overall, including their race and gender. The most uniquely mentioned person in the Mainstream collection is George Washington; in the Diversity collection, it is Martin Luther King Junior. For the Mainstream collection, all five of the most commonly mentioned people are White males. For the Diversity collection, all five are males, two of whom are White (Abraham Lincoln, George Washington) and three of whom are Black (Martin Luther King Junior, Frederick Douglass, and Langston Hughes). Even in the Female collection, the three most uniquely mentioned people are males (Martin Luther King Junior, John F. Kennedy, and Jimmy Carter) and the fourth is a female (Betty Friedan).[60]

We then explore whether these trends in racial representation of famous people track the US population share of different races in Figure 10.[61] In the Mainstream collection, White people – particularly White males – have been consistently overrepresented, and Black people and Latinx people underrepresented, relative to their US population share.

Birthplace of famous figures. We next examine representation of famous figures in terms of their place of origin. Learning about real people from different parts of the world can expand a child's understanding of experiences beyond their own, and is another important dimension of diversity in educational content. We show the spatial distribution of birthplaces of famous figures mentioned in the Mainstream and Diversity collections in Figure 11, which presents a map of the world with a dot for each birthplace. This captures the representation of national and subnational identities presented to children. This figure shows that Mainstream

[60]Appendix Tables A2 and A3 show this for the top five females and top five males, respectively, uniquely mentioned in each collection. Appendix Table A4 shows the most uniquely mentioned famous figure by collection for each decade. Out of all collections and decades, only two females are the most uniquely mentioned famous figures.

[61]These data come from the US census, which we explain in Section V.B.

collection books primarily feature famous figures from Europe and the eastern portion of the United States. By contrast, Diversity collection books feature famous figures from across the world and, more precisely, an order of magnitude more famous people from South America, Africa, and Asia.

We can also analyze how the birthplace of famous people presented in these books varies by gender, another way of studying the representation of intersectionality. Appendix Figure A10 shows that males have more geographic heterogeneous representation in terms of birthplaces than females across both the Mainstream and Diversity collections. Females that are represented are far more likely to be from North America (primarily the United States) and Europe than males, who, particularly in the Diversity collection, come from many more parts of the world.

Words related to nationality and color. We next look at the construct of race in text by examining the proportion of words related to nationalities (e.g., Kenyan, Indian, Canadian) and colors (e.g., black, white, blue) in Appendix Figure A11. This method, while more straightforward than our other analyses, serves as a barometer for our other measures of race and helps illustrate what a simpler approach to content analysis might have yielded. The collection of books that recognize the Black or African American experience is much more likely to mention the words black and white. We then look at mentions of non-race colors such as red and blue as a falsification exercise. They are a negligible proportion of words overall and this is consistent over time.

The findings we present in this section highlight a key pattern we find throughout this analysis: the low representation of intersectional experiences – for example, the experience of Black women – even in collections which are deliberately chosen for their diversity in representation. We observe two related phenomena: one, the failure of the collections focusing on race to be equitably gender-representative; and two, the relatively lower performance of the collections which focus on identities other than those related to race (such as the Female collection) to center the experiences of race in their books.

VI.B Representation of Gender Identity

We characterize the representation of gender using (1) the numbers of gendered tokens in the text, (2) the predicted gender of character first names in the text, (3) the gender of famous figures in the text, and (4) the predicted gender classification of the detected character faces in images.[62] We present patterns for these measures of representation, and conclude by comparing the representation of gender in images to that in text.

[62]We describe the methods for each of these in Section IV (1 – 3) and Section III (4).

All gendered words. We first report the patterns for an aggregated measure of the textual representation of gender, which includes all counts of gendered tokens, the gender of the famous characters in the text, and the gender classifications for character first names. In Figure 12, we present estimates of the book-level proportion of the gendered words and characters which are female. In Figure 12a, we show the distribution of these estimates for the Mainstream and Diversity collections.[63] In Figure 12b, we show this distribution for each of the collections, including the smaller collections that highlight specific identities. We observe that the Mainstream collection is the most male-skewed of all the collections. The patterns show that in all collections except the Female collection, the central tendency of each distribution is skewed towards more male representation. However, we see that the Female collection – which we would expect to be more female-centered – is less female-skewed than the Mainstream collection is male-skewed.

In Figures 13a, 13b, and 13c, we present a numerical accounting of the proportion of female words relative to all gendered words. The main pattern we observe is that, for all collections except those books specifically recognized for highlighting females, fewer female words are present than male words. Figure 13a shows that the proportion of female words in these collections is between 35 and 45 percent, as opposed to 56 percent in the Female collection. Figure 13b presents the ratio of male words to female words as opposed to just the proportion and documents that this pattern of greater male representation is consistent across time for collection and decade book averages. Figure 13c shows that this proportion is gradually increasing over time but remains below the US population share of females for all collections in every decade, except for the Female collection.

One possible dimension on which the representation of gender might vary is by type of gendered word. For example, until recently, grammar rules dictated that male pronouns would be used as "gender-neutral" pronouns, which would then lead us to overstate the male representation in these books. However, the pattern holds when the analysis is restricted to each type of gendered word: pronouns, specific gendered tokens such as "princess" and "prince," gendered first names of characters, or gender of famous people mentioned (Appendix Figure A12).

These patterns of discrepancy in the representation of gender in text are consistent across other measures of gender representation, such as whether they are represented as individuals or groups of females vs. males (Appendix Figure A13) or if they are represented as the subject (as opposed to the object) of a sentence (Appendix Figure A14).

[63]Recall that the Diversity collection is the aggregate of multiple smaller collections which focus on centering different diverse identities. The classification is shown in Figure 1a.

Gender of famous figures. A related but distinct parameter is the number of female and male famous figures mentioned in these books. The specific people who are named in a book transmit more implicit information to a child beyond generic tokens. By naming these individuals, they take on a greater significance to children. This can influence both child aspiration, as in the role model effects studied in Dee (2005) and Porter and Serra (2020), as well as social preferences and beliefs more generally (Plant et al., 2009; Alrababah et al., Forthcoming). We show our collection-specific estimates of this parameter in Figure 13d. On this dimension, inequality in representation of gender is much more severe. In the Mainstream collection, 86 percent of the famous figures mentioned across all books were male, for example. Even the Female collection ceases to be more representative of women than of men (Appendix Figure A12 shows that not even one-third of the historical figures mentioned across all books were female. However, when famous females were present, they were mentioned more often). Furthermore, two collections (LGBTQ and Diversity) contain similar average proportions of characters who are female as contained in the Female collection.

Gender of pictured characters. Next, we describe the representation of gender in the images of these books. We show the proportion of faces in each collection identified as female in Appendix Figure A6a. In the majority of the collections, fewer than half of the detected faces are classified as female-presenting. In the Female collection, however, we classify 70 percent of the faces as female, and in the Ability collection, we classify 60 percent of the faces as female. Appendix Figure A6b shows that, unlike for text, there is no obvious trend in gender representation in images, within collections over time.[64,65]

Gender in images and text. We then compare representation of gender across images and text. In Figure 14a, we show a scatterplot of collection-by-decade average proportions of female words on the x-axis and the average proportion of female-presenting faces on the y-axis. It shows that for females, the representation of females in gendered words is less equal than the representation of females in images. In other words, females are more likely to be visualized (seen) than mentioned in the text (heard). This suggests that authors or illustrators may perfunctorily include additional females in pictures, giving the appearance of equity while not actually having them play an important role in the story. Importantly, it also shows that on average, females are represented less than half of the time in both

[64]We show a similar pattern when using a continuous measure of the average probability that a face is classified as being female in Appendix Figure A15.

[65]In Appendix Figure A16, we examine the representation of skin color by gender by showing the perceptual tint of faces, separated by their detected gender. In images, we find no evidence of a (perceptible) difference between classified females and males in terms of the frequency of different skin tones represented.

images and text.[66] Figure 14b shows the converse of this for males, underscoring that they are represented more than half of the time in both images and text.

VI.C Representation of Age

Finally, we briefly discuss the representation of people by age in the images and text of our books. In Figure 15a, we show detected character faces by age and gender. We find that images of males dominate in most collections, though in no case is the discrepancy as extreme as it is in gendered adults in text. In the Female and Ability collections, there are more females than males. Regardless of gender, in both images and text, we show that there are more adults than children depicted in the books in each collection.[67] We also see in Appendix Figure A7c that adults are overrepresented relative to their share in the census. This raises a question as to why adult experiences or depictions are privileged in books targeted to children.

In Figure 15b, we show the age classifications of gendered words (e.g., girl vs. woman and boy vs. man). Similar to images, this shows that, in most books, the distribution of young people by gender is roughly similar, though in the Female collection, girls are roughly twice as likely to appear than boys. For words specific to gendered adults, however, men are always more likely to appear. This discrepancy is largest in the Mainstream and African American collections, where adult men are roughly 60 percent of adult gendered mentions and adult women only 40 percent.

We also study how the representation of skin color varies by age. Figures 16a and 16b present plots of the distribution and percentage of skin color tints which show that when children are depicted in images, they are more likely to be shown with lighter skin tone than adults, regardless of collection.[68] We are aware of no definitive biological justification for this systematic difference in the representation of skin colors by age. There are many possible determinants of potential differences, for example, greater exposure to the sun from more outside labor could cause adults to be darker. Mixed race couples may generate children who are lighter, on average, than the mean of the parent's skin tone. On the other hand, evidence of the breakdown of melanin over the life course (Sarna et al., 2003) suggests that there may be reason to expect the skin tone of adults to be lighter than that of children.

[66] In Appendix Figure A17, we show these results for females by race in which we see Black and Latinx females less represented.

[67] One concern may be that the age classification algorithms are primarily trained on adult faces, and therefore overclassify adults; however, we see consistent ratios of adult presence to children presence in text and in images.

[68] One concern could be that the algorithms are trained to classify faces as being more likely to be a child if the skin color of the detected face is lighter, which then would attenuate the number of children detected.

Nonetheless, the pattern we find of children being represented with lighter skin than adults is consistent across collections. While there are many potential interpretations of this pattern, a particularly concerning one is that brightness may be used to connote innocence (e.g., of childhood), supernatural features (e.g., of angels), or another type of emphasis which separates the character from the rest of the context.

VII AI is Only Human

Our paper brings a set of artificial intelligence tools to bear on the field of content analysis. These tools are powerful, computer-driven methods. They are designed by humans and, in many cases, trained with initial human input. We use them because they offer a few key advantages. The first is scale: because algorithms are automated, they allow for analysis of a much larger set of content than would be possible using conventional, "by hand" methods. The second is adaptability: we can rapidly change one dimension of measurement and re-run the analysis at low cost. Were we to do this via hand-coding, the cost would increase linearly with each addition or adjustment (see Section VIII); with AI-based analysis, the marginal cost of such additions or adjustments is much lower.

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. To address this, we trained our own face detection model using 5,403 illustrated faces from the Caldecott and Newbery corpora (discussed in Section III.A). 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 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 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, this problem is also intrinsic to traditional "by-hand" content analysis. Manual coding necessarily can only reflect the biases of the individual coders. We observed that the identities of the manual labelers on our team led to non-classical 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 measurement error. For example, in addition to the manually coded putative race of famous figures, we examine two other constructs of race – birthplace of famous figures and 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.

VIII Cost-Effectiveness

Drawing from validation theory, we conducted traditional manual content analysis 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. This helped

us to evaluate the plausibility of our measures and also identify messages our tools fail to detect, clarifying limitations of computer-led content analysis.

It took approximately 40 hours to code the entire book (400 pages at an average of 6 minutes per page).[69] 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.

Regardless of whether we use manual coding or computer vision, the broad patterns are the same. We show results comparing the hand coded representations to the computer vision representations in Appendix Figures A18 and A19. Over 50 percent of the characters and gendered words are male and the skin colors depicted are skewed away from darker-skinned individuals.

IX Summary and Concluding Remarks

The books we use to educate our children teach them about the world in which they live. The way that people are – or are not – portrayed in these books demonstrates who can inhabit different roles within this world and can shape subconscious defaults. Historical and persistent inequality, both by race and gender and in other dimensions, can be either affirmed or challenged by what we teach children about the world. While many educators and schools wish to eliminate materials that have overt racial and gender bias and use content that promotes positive messages about all people, such efforts are necessarily piecemeal and the judgments behind them subjective. Per the adage "a picture is worth a thousand words," images in particular convey numerous messages. Social scientists are leaving data on the table by not systematically measuring the content of these messages implicitly and explicitly being sent to children through these visual depictions which, previously, had not been quantified systematically.

In this paper, we make two primary contributions. First, we introduce machine-led computer vision methods to convert images into data on skin color, putative race, gender, and age of pictured characters. Second, we apply these image analysis tools – in addition to established natural language processing methods that analyze text – to award-winning children's books to document the representations to which children have been exposed over the last century. We analyze these books by the purposes of their award categories, broadly

[69] 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.

categorizing them as Mainstream collections if they were selected without explicit intention to highlight a specific identity and as Diversity collections if they were deliberately chosen for a given award because of their focus on underrepresented groups. We then further create smaller collections that highlight specific identities.

We show suggestive evidence from public library checkout data that children may be twice as likely to be exposed to books from the Mainstream collection relative to other books. This illustrates the outsized influence that Newbery and Caldecott honorees may have and highlights the importance of understanding what messages children may be encountering in these books.

These image analysis tools show that books selected to highlight people of color or females increasingly depict characters with darker skin tones over time. Books in the Mainstream collection, however, primarily depict characters with lighter skin tones compared to books in the other collections, despite increased rhetoric about the importance of representation. Moreover, we see that children consistently have been more likely than adults to be depicted with light skin. Regardless of the reason, these findings show that lighter-skinned children see themselves represented more often in these books than do darker-skinned children.

We compare the patterns we find in images to those we find in text. We see that females are more likely to be represented in images than in text over time, consistent with the maxim that women should "be seen but not heard." This suggests there may be symbolic inclusion in pictures without substantive inclusion in the actual story. Across all measures in our study, males, especially White males, are persistently more likely to be represented; this overrepresentation relative to their share in the US population is surprising, particularly given substantial changes in female societal participation over time.

Our approach has a few key limitations. First, artificial intelligence tools reflect the biases of the human coders that trained the models, in ways distinct from but consistent with traditional content analysis conducted entirely manually. Second, the measures of representation that we use are imperfect. Our measures of gender identity neglect measurement of non-binary and gender-fluid identities. Because race is a multifaceted construct of human categorization that is ill-defined, efforts to measure it are inherently difficult. Third, the algorithms we use do not perfectly detect faces or isolate the skin from faces, generating measurement error. Fourth, our analysis consists of a numerical accounting of different characters through simple representational statistics, i.e., *whether* characters are included. However, this is not a holistic measure of representation. If a character is depicted in a

reductive or stereotypical manner, then their representation may send messages which inadvertently reinforce existing inequality in representation. An important avenue for future work will be to further develop tools that can measure *how* people are represented and thus capture the messages sent by the manner of their portrayal as well as its incidence.

The "optimal" level of representation is a normative question beyond the scope of this paper, but the actual representation in books is something that can be measured and, given some reasonable set of goals, improved upon. To achieve any progress toward such goals, practitioners and publishers require mechanisms to systematically measure and compare the amount and type of representation in the content they consider for inclusion in curriculum or even for prospective consideration for publication.

Inequality in representation, particularly in the materials we use to teach children, is a systemic problem which requires a systemic solution. Our tools will directly contribute to lasting improvement of the practice of education, both by helping guide curriculum choices and by assisting publishers and content creators to prospectively assess representation in the creation of new content. Separately, these tools can help catalyze a wide range of scholarship to systematically use printed content – images, as well as text – as primary source data. This work could, for example, describe patterns of representation in other bodies of content and, subsequently, study how variation in representation shapes human beliefs, behavior, and outcomes. Finally, these methods can be applied to the study of other text and visual media, from print-based and online news to television and film. By providing research that expands our understanding about the diversity in content, we can help to contribute to work that aims to overcome the structural inequality that pervades society and our daily lives.

References

Alrababah, Ala, William Marble, Salma Mousa, and Alexandra Siegel. Forthcoming. "Can exposure to celebrities reduce prejudice? The effect of Mohamed Salah on Islamophobic behaviors and attitudes." American Political Science Review.

ALSC. 2007. "The Newbery and Caldecott Awards: A guide to the Medal and Honor books." Association for Library Service to Children, American Library Association.

Appadurai, Arjun. 2004. "The capacity to aspire: Culture and the terms of recognition." Culture and public action, 59: 62–63.

Apple, Michael, and Linda Christian-Smith. 1991. The politics of the textbook. Routledge.

Balter, Rochelle. 1999. "From stigmatization to patronization: The media's distorted portrayal of physical disability." American Psychological Association.

Banks, Taunya Lovell. 1999. "Colorism: A darker shade of pale." UCLA L. Rev., 47: 1705.

Beaman, Lori, Esther Duflo, Rohini Pande, and Petia Topalova. 2012. "Female leadership raises aspirations and educational attainment for girls: A policy experiment in India." Science, 335(6068).

Bell, Philip. 2001. "Content analysis of visual images." In The Handbook of Visual Analysis. Chapter 2, 11–34. Thousand Oaks, CA:Sage.

Bertrand, Marianne, Dean Karlan, Sendhil Mullainathan, Eldar Shafir, and Jonathan Zinman. 2010. "What's advertising content worth? Evidence from a consumer credit marketing field experiment." The Quarterly Journal of Economics, 125(1): 263–306.

Beyer, Lucas. 2018. "Github: PyDenseCRF."

Blau, Francine D, and Lawrence M Kahn. 2017. "The gender wage gap: Extent, trends, and explanations." Journal of Economic Literature, 55(3): 789–865.

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.

Brooks, Dwight E, and Lisa P Hébert. 2006. "Gender, race, and media representation." Handbook of Gender and Communication, 16.

Brooks-Gunn, Jeanne, Greg J Duncan, Pamela Kato Klebanov, and Naomi Sealand. 1993. "Do neighborhoods influence child and adolescent development?" American Journal of Sociology, 99(2): 353–395.

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

Burchfield, Marcy, Henry G Overman, Diego Puga, and Matthew A Turner. 2006. "Causes of sprawl: A portrait from space." The Quarterly Journal of Economics, 121(2): 587–633.

Burton, Linda M, Eduardo Bonilla-Silva, Victor Ray, Rose Buckelew, and Elizabeth Hordge Freeman. 2010. "Critical race theories, colorism, and the decade's research on families of color." Journal of Marriage and Family, 72(3): 440–459.

Caliskan, Aylin, Joanna J Bryson, and Arvind Narayanan. 2017. "Semantics derived automatically from language corpora contain human-like biases." Science, 356(6334).

Cantoni, Davide, Yuyu Chen, David Y Yang, Noam Yuchtman, and Y Jane Zhang. 2017. "Curriculum and ideology." Journal of Political Economy, 125(2): 338–392.

Cappelen, Alexander, John List, Anya Samek, and Bertil Tungodden. 2020. "The effect of early-childhood education on social preferences." Journal of Political Economy, 128(7): 2739–2758.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment." American Economic Review, 106(4): 855–902.

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. 2020. "Race and economic opportunity in the United States: An intergenerational perspective." The Quarterly Journal of Economics, 135(2): 711–783.

Cockcroft, Marlaina. 2018. "Caldecott and Newbery Medal wins bring instant boost to book sales." School Library Journal, 64(2).

Crenshaw, Kimberlé. 1989. "Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics." University of Chicago Legal Forum, 1989(8).

Crenshaw, Kimberlé. 1990. "Mapping the margins: Intersectionality, identity politics, and violence against women of color." Stanford Law Review, 43: 1241.

Cutler, David M, and Edward L Glaeser. 1997. "Are ghettos good or bad?" The Quarterly Journal of Economics, 112(3): 827–872.

Daniels, Elizabeth A, Marlee C Layh, and Linda K Porzelius. 2016. "Grooming ten-year-olds with gender stereotypes? A content analysis of preteen and teen girl magazines." Body Image, 19.

Darity, William A, and Patrick L Mason. 1998. "Evidence on discrimination in employment: Codes of color, codes of gender." Journal of Economic Perspectives, 12(2): 63–90.

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.

Dee, Thomas S. 2004. "Teachers, race, and student achievement in a randomized experiment." Review of Economics and Statistics, 86(1): 195–210.

Dee, Thomas S. 2005. "A teacher like me: Does race, ethnicity, or gender matter?" American Economic Review, 95(2): 158–165.

Dixon, Angela R, and Edward E Telles. 2017. "Skin color and colorism: Global research, concepts, and measurement." Annual Review of Sociology, 43: 405–424.

Dobrow, Julia R, and Calvin L Gidney. 1998. "The good, the bad, and the foreign: The use of dialect in children's animated television." The Annals of the American Academy of Political and Social Science, 557(1).

Eble, Alex, and Feng Hu. 2020. "Child beliefs, societal beliefs, and teacher-student identity match." Economics of Education Review, 77: 101994.

Fuchs-Schündeln, Nicola, and Paolo Masella. 2016. "Long-lasting effects of socialist education." Review of Economics and Statistics, 98(3): 428–441.

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.

Garg, Nikhil, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. "Word embeddings quantify 100 years of gender and ethnic stereotypes." Proceedings of the National Academy of Sciences, 115(16): E3635–E3644.

Genicot, Garance, and Debraj Ray. 2017. "Aspirations and inequality." Econometrica, 85(2): 489–519.

Gentzkow, Matthew, and Jesse M Shapiro. 2010. "What drives media slant? Evidence from US daily newspapers." Econometrica, 78(1).

Gentzkow, Matthew, Bryan T. Kelly, and Matt Taddy. 2019. "Text as data." Journal of Economic Literature, 57(3): 535–74.

Gentzkow, Matthew, Jesse M Shapiro, and Matt Taddy. 2019. "Measuring group differences in high-dimensional choices: Method and application to Congressional speech." Econometrica, 87(4): 1307–1340.

Gershenson, Seth, Cassandra Hart, Joshua Hyman, Constance Lindsay, and Nicholas W Papageorge. 2018. "The long-run impacts of same-race teachers." National Bureau of Economic Research.

Ghavami, Negin, Dalal Katsiaficas, and Leoandra Onnie Rogers. 2016. "Toward an intersectional approach in developmental science: The role of race, gender, sexual orientation, and immigrant status." In Advances in Child Development and Behavior. Vol. 50, 31–73. Elsevier.

Gibson, Campbell, and Kay Jung. 2002. "Historical census statistics on population totals by race, 1790 to 1990, and by Hispanic origin, 1790 to 1990, for the United States, regions, divisions, and states."

Giroux, Henry A. 1981. Ideology, culture, and the process of schooling. Temple University Press.

Han, Ted, and Amanda Hickman. 2019. "Our search for the best OCR tool, and what we found."

Henderson, J Vernon, Adam Storeygard, and David N Weil. 2012. "Measuring economic growth from outer space." American Economic Review, 102(2): 994–1028.

Hersch, Joni. 2008. "Profiling the new immigrant worker: The effects of skin color and height." Journal of Labor Economics, 26(2): 345–386.

Hunter, Margaret. 2007. "The persistent problem of colorism: Skin tone, status, and inequality." Sociology Compass, 1(1): 237–254.

Jackson, Aaron S, Michel Valstar, and Georgios Tzimiropoulos. 2016. "A CNN cascade for landmark guided semantic part segmentation." European Conference on Computer Vision, 143–155.

Jansen, JD. 1997. "Critical theory and the school curriculum." Metatheories in Educational Theory and Practice.

Jencks, Christopher, and Susan E Mayer. 1990. "The social consequences of growing up in a poor neighborhood." Inner-city Poverty in the United States, 111: 186.

Jensen, Robert, and Emily Oster. 2009. "The power of TV: Cable television and women's status in India." The Quarterly Journal of Economics, 124(3).

Kane, Michael T. 2013. "Validating the interpretations and uses of test scores." Journal of Educational Measurement, 50(1).

Kearney, Melissa S, and Phillip B Levine. 2019. "Early childhood education by television: Lessons from Sesame Street." American Economic Journal: Applied Economics, 11(1): 318–50.

Keith, Verna M, and Carla R Monroe. 2016. "Histories of colorism and implications for education." Theory Into Practice, 55(1): 4–10.

Knowles, Elizabeth, Liz Knowles, and Martha Smith. 1997. The reading connection: Bringing parents, teachers, and librarians together. Libraries Unlimited.

Koss, Melanie D, and Kathleen A Paciga. 2020. "Diversity in Newbery Medal-winning titles: A content analysis." Journal of Language and Literacy Education, 16(2): n2.

Koss, Melanie D, Nancy J Johnson, and Miriam Martinez. 2018. "Mapping the diversity in Caldecott books from 1938 to 2017: The changing topography." Journal of Children's Literature, 44(1): 4–20.

Kozlowski, Austin C, Matt Taddy, and James A Evans. 2019. "The geometry of culture: Analyzing the meanings of class through word embeddings." American Sociological Review, 84(5).

Krippendorff, Klaus. 1980. "Validity in content analysis." In Computerstrategien fÃr die kommunikationsanalyse. 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.

La Ferrara, Eliana, Alberto Chong, and Suzanne Duryea. 2012. "Soap operas and fertility: Evidence from Brazil." American Economic Journal: Applied Economics, 4(4): 1–31.

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

Leventhal, Tama, and Jeanne Brooks-Gunn. 2000. "The neighborhoods they live in: The effects of neighborhood residence on child and adolescent outcomes." Psychological Bulletin, 126(2): 309.

Lewis, Randall A, and Justin M Rao. 2015. "The unfavorable economics of measuring the returns to advertising." The Quarterly Journal of Economics, 130(4): 1941–1973.

Lu, Conny. 2018. "Github: Face segmentation with CNN and CRF."

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

MacMaster, Neil. 2001. Racism in Europe: 1870-2000. New York, NY:Palgrave.

Martin, Ardis C. 2008. "Television media as a potential negative factor in the racial identity development of African American youth." Academic Psychiatry.

Marx, David M, Sei Jin Ko, and Ray A Friedman. 2009. "The "Obama effect": How a salient role model reduces race-based performance differences." Journal of Experimental Social Psychology, 45(4): 953–956.

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.

Monk Jr, Ellis P. 2015. "The cost of color: Skin color, discrimination, and health among African-Americans." American Journal of Sociology, 121(2): 396–444.

Muhammad, Khalil Gibran. 2019. The condemnation of Blackness: Race, crime, and the making of modern urban America, with a new preface. Cambridge, MA:Harvard University Press.

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.

O'Flaherty, Brendan. 2015. The Economics of Race in the United States. Cambridge, MA:Harvard University Press.

O'Kelly, Charlotte G. 1974. "Sexism in children's television." Journalism Quarterly, 51(4).

Paceley, Megan S, and Karen Flynn. 2012. "Media representations of bullying toward queer youth: Gender, race, and age discrepancies." Journal of LGBT Youth, 9(4).

Pathak, Madhu A, Kowichi Jimbow, George Szabo, and Thomas B Fitzpatrick. 1976. "Sunlight and melanin pigmentation." Photochemical and Photobiological Reviews, 211–239.

Plant, E Ashby, Patricia G Devine, William TL Cox, Corey Columb, Saul L Miller, Joanna Goplen, and B Michelle Peruche. 2009. "The Obama effect: Decreasing implicit prejudice and stereotyping." Journal of Experimental Social Psychology, 45(4): 961–964.

Porter, Catherine, and Danila Serra. 2020. "Gender differences in the choice of major: The importance of female role models." American Economic Journal: Applied Economics, 12(3): 226–54.

Quillian, Lincoln, Devah Pager, Ole Hexel, and Arnfinn H Midtbøen. 2017. "Meta-analysis of field experiments shows no change in racial discrimination in hiring over time." Proceedings of the National Academy of Sciences, 114(41): 10870–10875.

Riley, Emma. 2017. "Increasing students' aspirations: The impact of Queen of Katwe on students' educational attainment." In CSAE Working Paper WPS/2017-13.

Sampson, Robert J, Jeffrey D Morenoff, and Thomas Gannon-Rowley. 2002. "Assessing "neighborhood effects": Social processes and new directions in research." Annual Review of Sociology, 28(1): 443–478.

Sarna, Tadeusz, Janice M Burke, Witold Korytowski, Małgorzata Różanowska, Christine MB Skumatz, Agnieszka Zaręba, and Mariusz Zaręba. 2003. "Loss of melanin from human RPE with aging: Possible role of melanin photooxidation." Experimental Eye Research, 76(1): 89–98.

Sculley, David. 2010. "Web-scale k-means clustering." Proceedings of the 19th International World Wide Web Conference, 1177–1178.

Smith, Vicky. 2013. "The 'Caldecott effect'." Children and Libraries: The Journal of the Association for Library Service to Children, 1(1): 9–13.

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

Steele, Claude M. 2010. Whistling Vivaldi: And Other Clues to How Stereotypes Affect Us (Issues of our Time). WW Norton & Company.

Steele, Claude M, and Joshua Aronson. 1995. "Stereotype threat and the intellectual test performance of African Americans." Journal of Personality and Social Psychology, 69(5): 797–811.

Stewig, John Warren, and Mary Lynn Knipfel. 1975. "Sexism in picture books: What progress?" The Elementary School Journal, 76(3).

Stout, Jane G, Nilanjana Dasgupta, Matthew Hunsinger, and Melissa A McManus. 2011. "STEMing the tide: Using ingroup experts to inoculate women's self-concept in science, technology, engineering, and mathematics (STEM)." Journal of Personality and Social Psychology, 100(2): 255.

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.

US Census. 2019. "Census QuickFacts." Accessed March 13, 2021.

Van Kleeck, Anne, Steven A Stahl, and Eurydice B Bauer. 2003. On Reading Books to Children: Parents and Teachers. Routledge.

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.

Wilson, William J. 2012. The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy. University of Chicago Press.

Witt, Susan D. 2000. "Review of research: The influence of television on children's gender role socialization." Childhood Education, 76(5): 322–324.

Yu, Amy Zhao, Shahar Ronen, Kevin Hu, Tiffany Lu, and César A Hidalgo. 2016. "Pantheon 1.0, a manually verified dataset of globally famous biographies." Scientific Data, 3(1): 1–16.

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

Zhou, Lei, Zhi Liu, and Xiangjian He. 2017. "Face parsing via a fully-convolutional continuous CRF neural network." CoRR, abs/1708.03736.

Zoph, Barret, and Quoc V Le. 2017. "Neural architecture search with reinforcement learning." arXiv.

X Tables

Table 1. Summary Statistics

	Mainstream	Diversity	People of Color	African American	Ability	Female	LGBTQ
Collection Totals							
Total Number of Books	495	635	577	130	29	14	15
Range of Years in our Sample	1923-2019	1971-2019	1971-2019	1971-2017	2000-2014	2013-2017	2010-2017
Book-Level Averages							
Number of Pages	139	148	137	147	213	314	268
Number of Words	24362	26497	23816	26328	35273	87411	55792
Number of Faces	44	58	60	41	30	30	73
% Faces - Human Skin Color	42%	46%	47%	43%	50%	45%	38%
% Faces - Monochromatic Skin Color	54%	48%	48%	52%	45%	54%	52%
% Faces - Non-Typical Skin Color	4%	6%	6%	6%	5%	1%	10%
Number of Famous People	2	8	7	2	0	1	0
Tint of All Faces	53	43	43	40	45	34	45
% Famous People Born in Africa	0%	2%	2%	2%	0%	16%	1%
% Famous People Born in Americas	56%	69%	70%	86%	69%	53%	71%
% Famous People Born in Asia	5%	7%	7%	2%	4%	8%	4%
% Famous People Born in Europe	38%	21%	21%	11%	26%	23%	24%
% Famous People Born in Oceania	1%	0%	0%	0%	0%	1%	0%

Note: In this table, we present summary statistics (described in the row titles) for each collection of books we analyze (named in the column titles).

Table 2. Measures of Representation

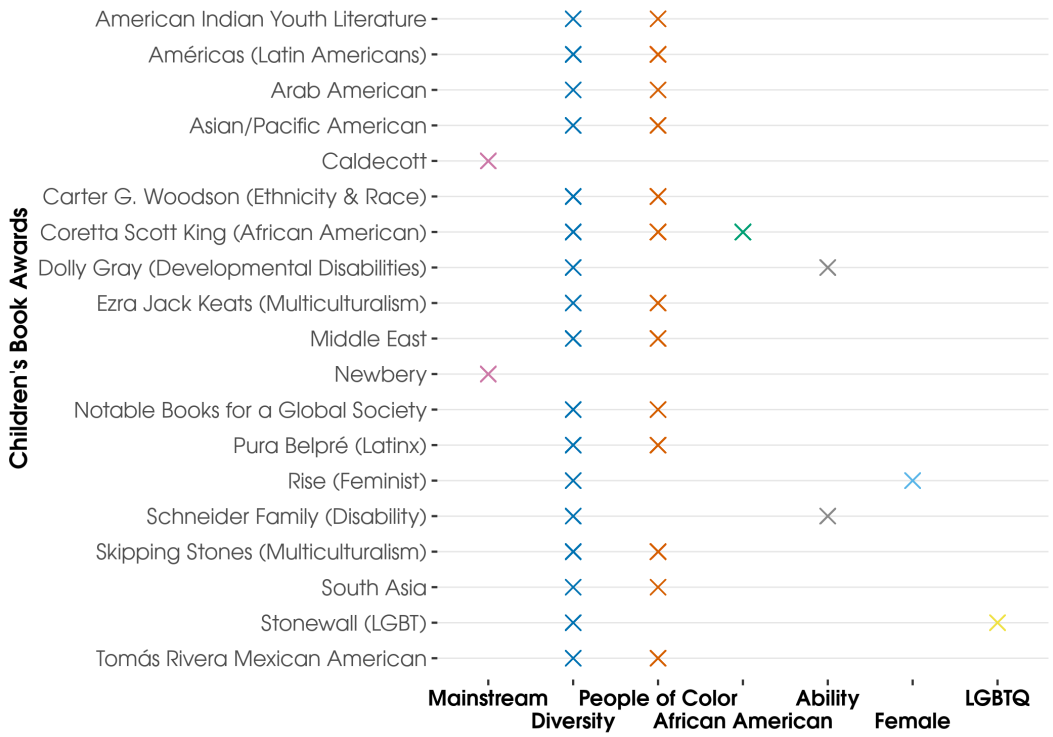
Measure	Image	Text
Race	• Skin color • Predicted race of face	• Race of famous figures • Birthplace of famous figures • Color token counts • Nationality token counts
Gender	• Predicted gender of face • Probability of gender of face	• Pronoun counts • Gendered token counts • Gender of famous figures • Predicted gender of first names
Age	• Predicted age of face	• Age-by-gender token counts

Note: In this table, we list the different variables we use to measure race, gender, and age in the faces in the images and, separately, the text in children's books.

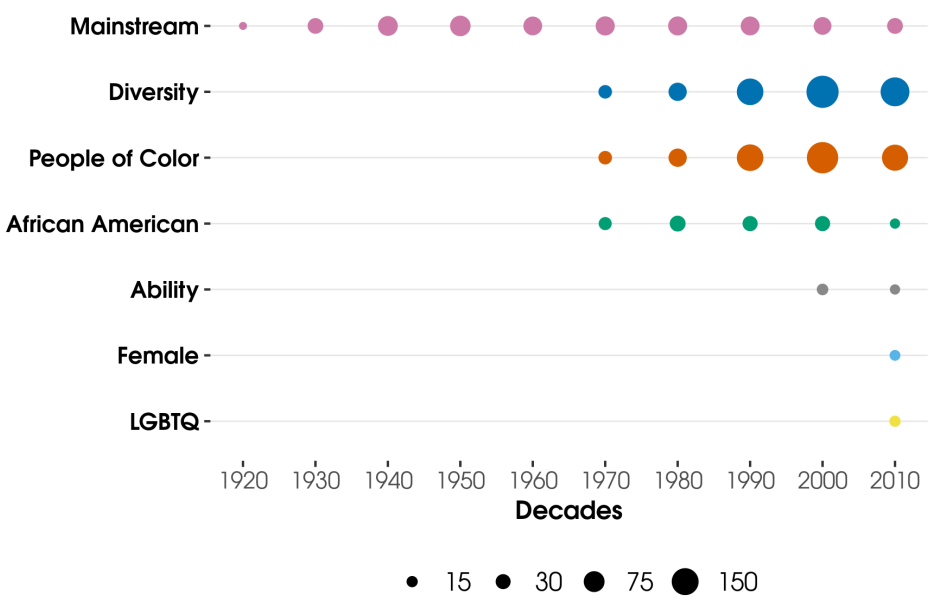
XI Figures

Figure 1. Books in the Sample

(a) Corpora in Sample, by Collection

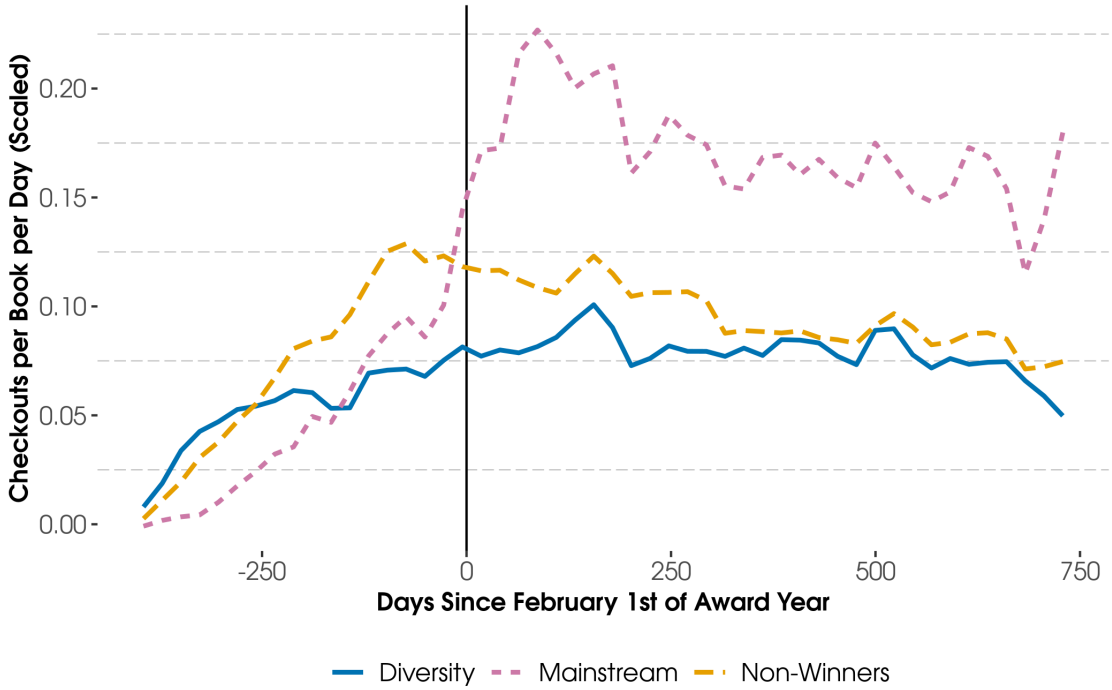


(b) Collection Sample Size, by Decade



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

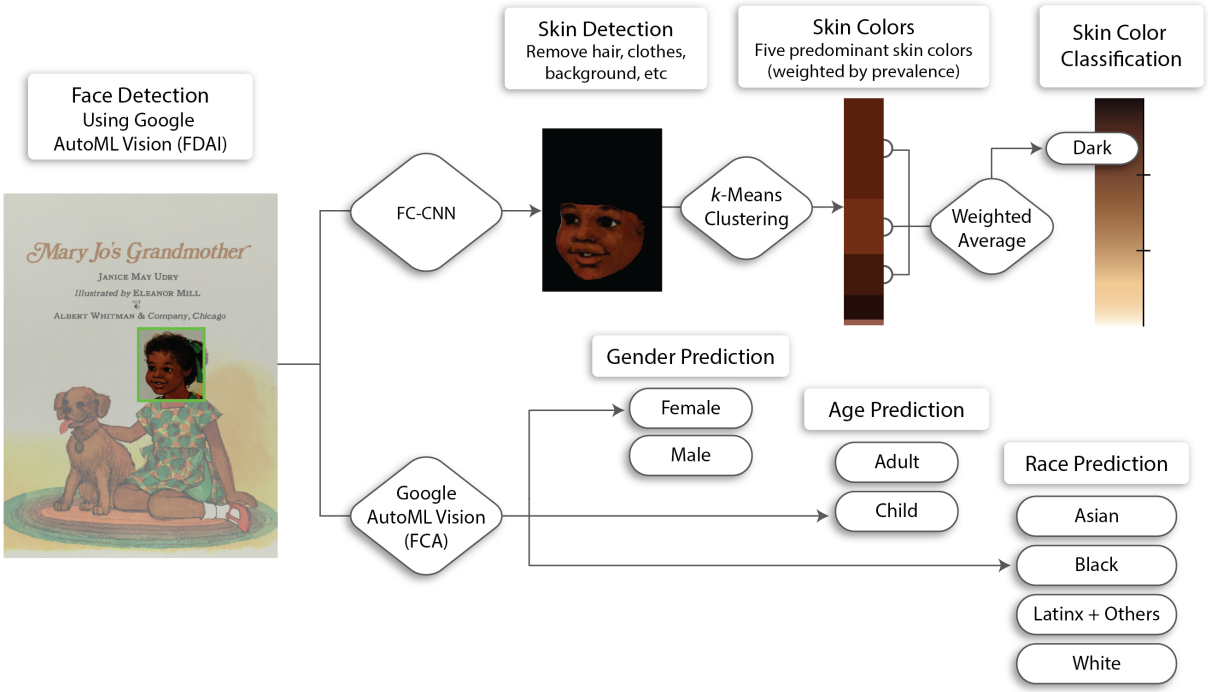
Figure 2. Children's Book Checkouts, by Collection



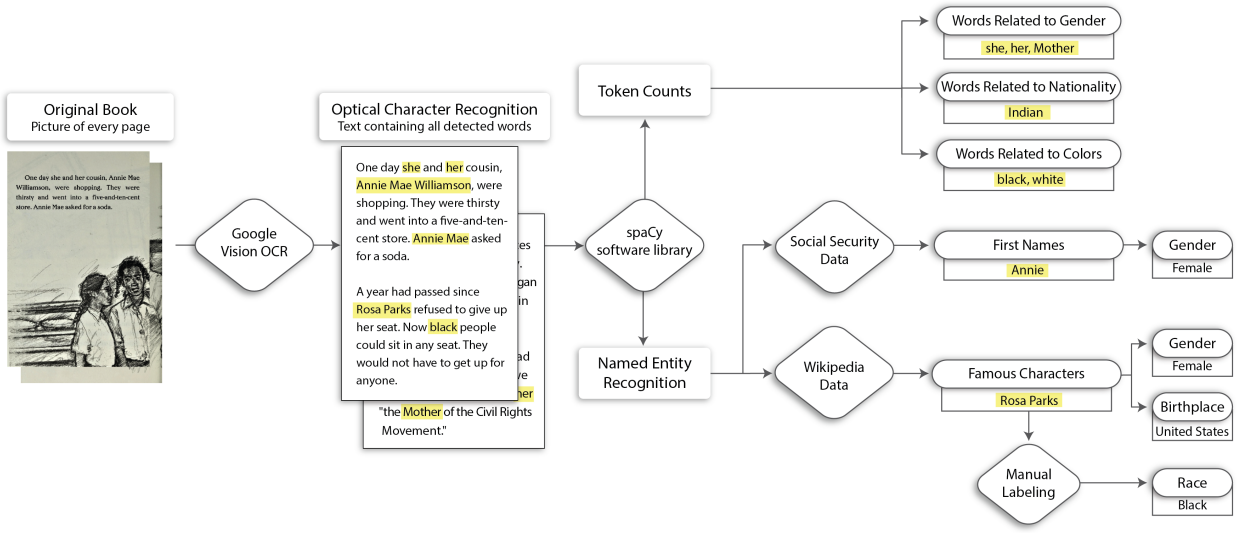
Note: In this figure, we show an event study of the average daily checkouts of children's library books between 2004 to 2017 from the Seattle Public Library, disaggregated by whether the book was recognized by a Mainstream award, a Diversity award, or whether it was a non-award winner. We use a smoothed local polynomial to generate each of the three series. See the data appendix for further discussion of our process for cleaning and aggregation of these data.

Figure 3. Converting Images and Text into Data

(a) Image-to-Data Pipeline



(b) Text-to-Data Pipeline



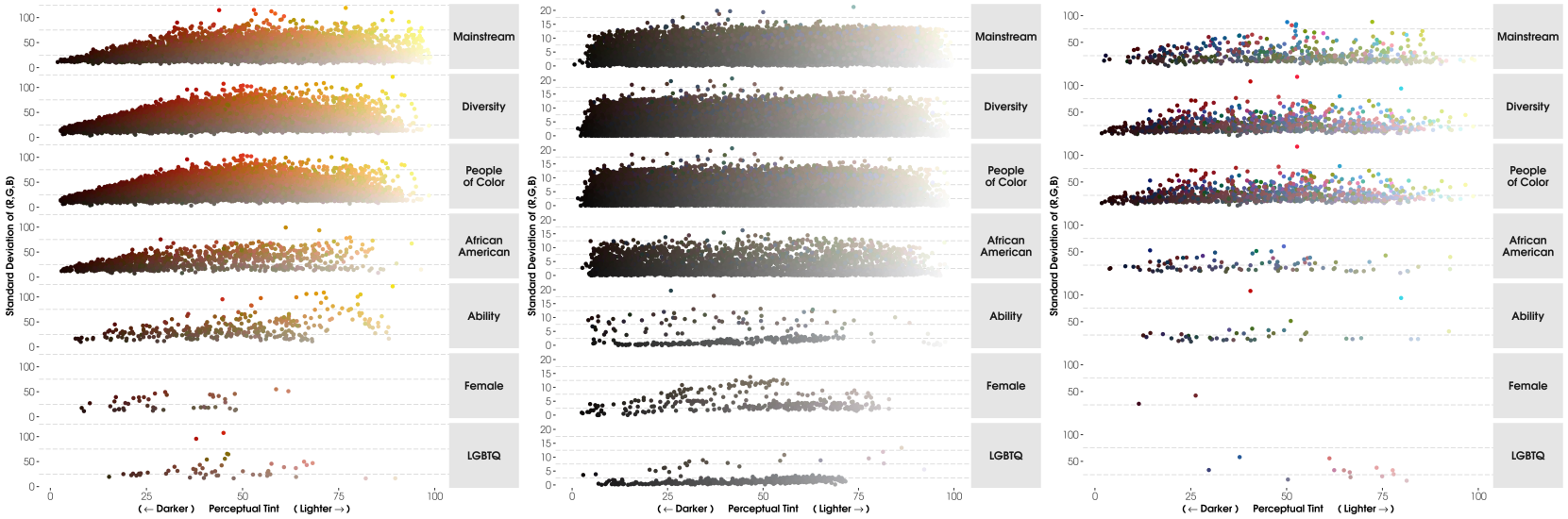
Note: In this figure, we show how we process scanned book pages into image and text data. In Panel A, we show how we extract image data and classify skin color, race, gender, and age. In Panel B, we show how we extract and isolate various dimensions of text, such as names of famous people or words related to gender.

Figure 4. Skin Color Data, by Color Type

(a) Human Skin Colors

(b) Monochromatic

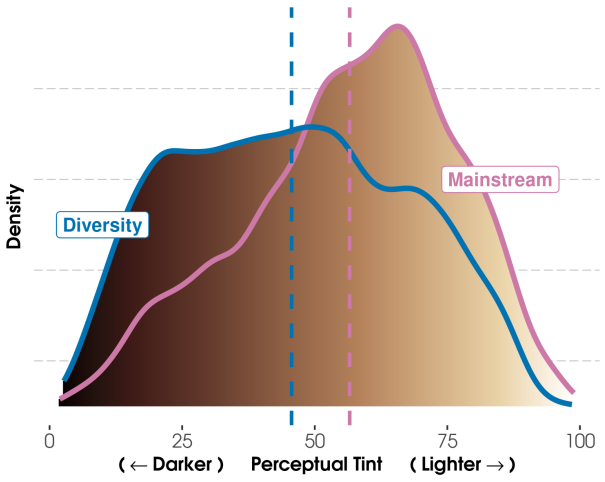
(c) Non-Typical Skin Colors



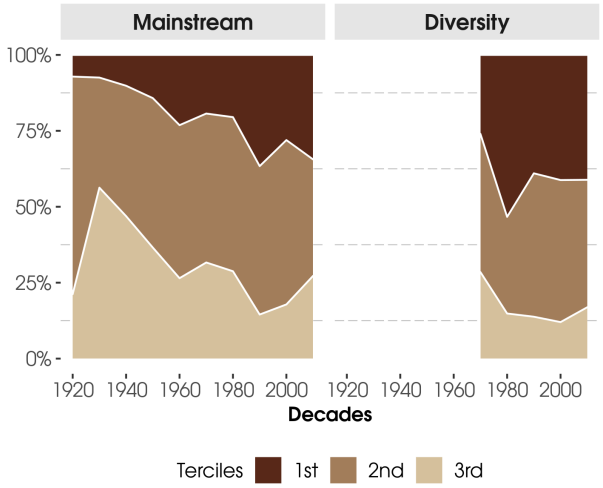
Note: This figure shows the representative skin colors of the individual faces we detect in the images found in the books from each collection. We show these by the three color "types" present in these images: human skin colors (polychromatic skin colors where R $\geq$ G $\geq$ B), monochromatic skin colors (e.g., black and white, sepia), and non-typical polychromatic skin colors (e.g., blue, green). The y-axis indicates the standard deviation of the RGB values of each face. The higher the standard deviation, the more vibrant the color.

Figure 5. Skin Colors in Faces, by Collection: Human Skin Colors

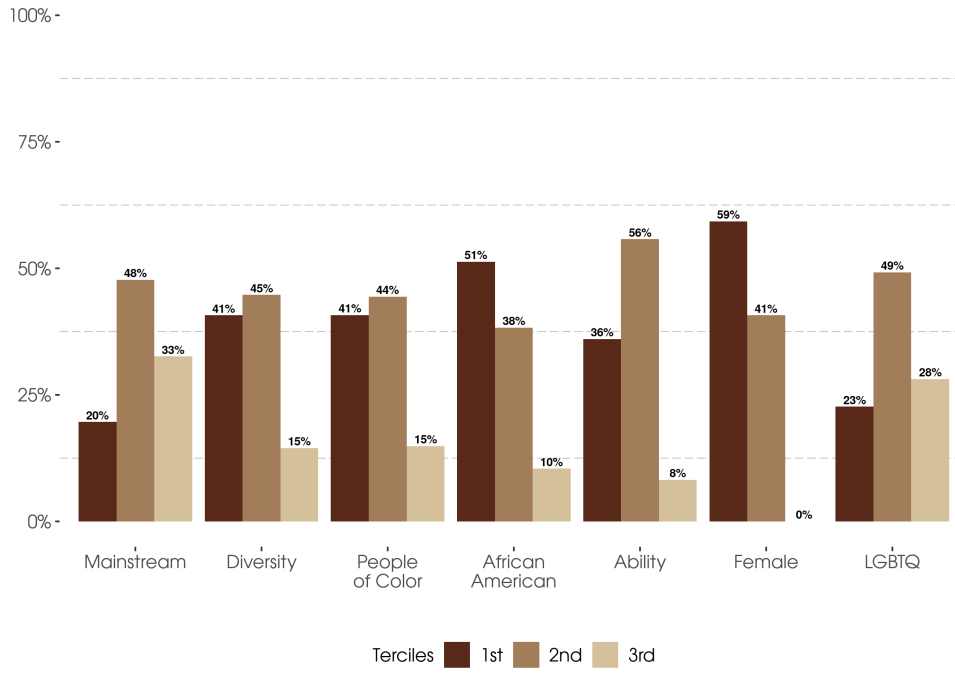
(a) Distribution of Skin Colors



(b) Mean Proportion in Each Tercile, Over Time



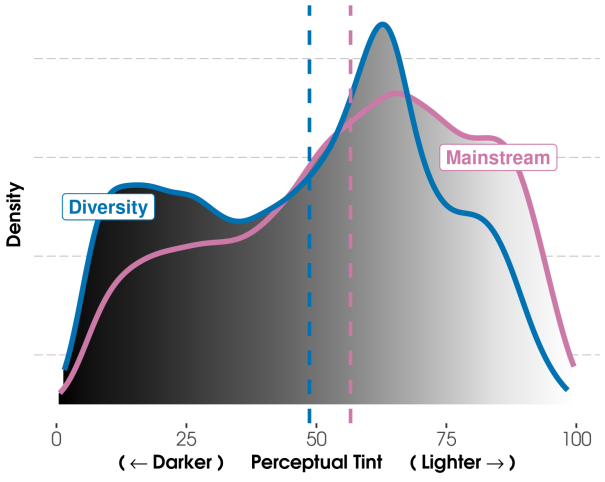
(c) Mean Proportion in Each Tercile, All Collections



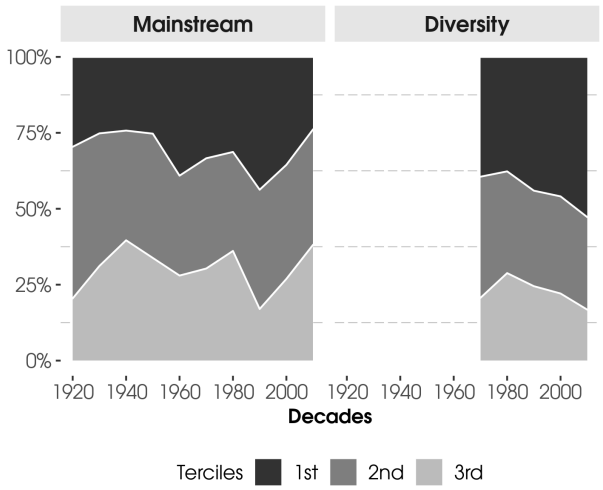
Note: This figure shows our analysis of the representative skin colors of the individual faces we detect in the images found in the books we analyze, focusing on faces considered to be human skin colors (polychromatic skin colors where $R \geq G \geq B$). Panel A shows the distribution of skin color 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 III.

Figure 6. Skin Colors in Faces, by Collection: Monochromatic Skin Colors

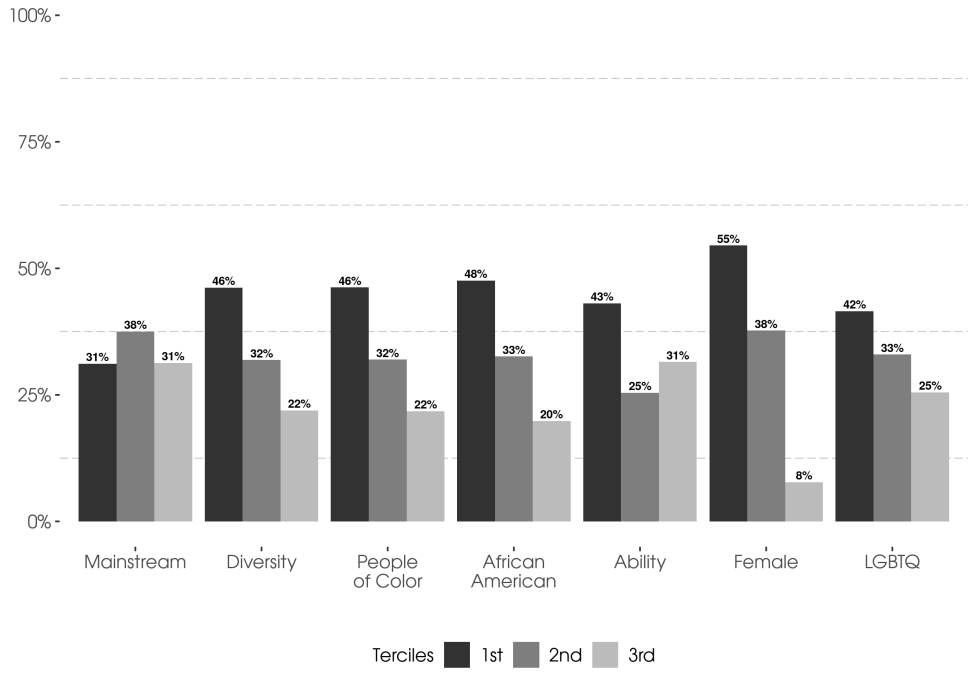
(a) Distribution of Skin Colors



(b) Mean Proportion in Each Tercile, Over Time

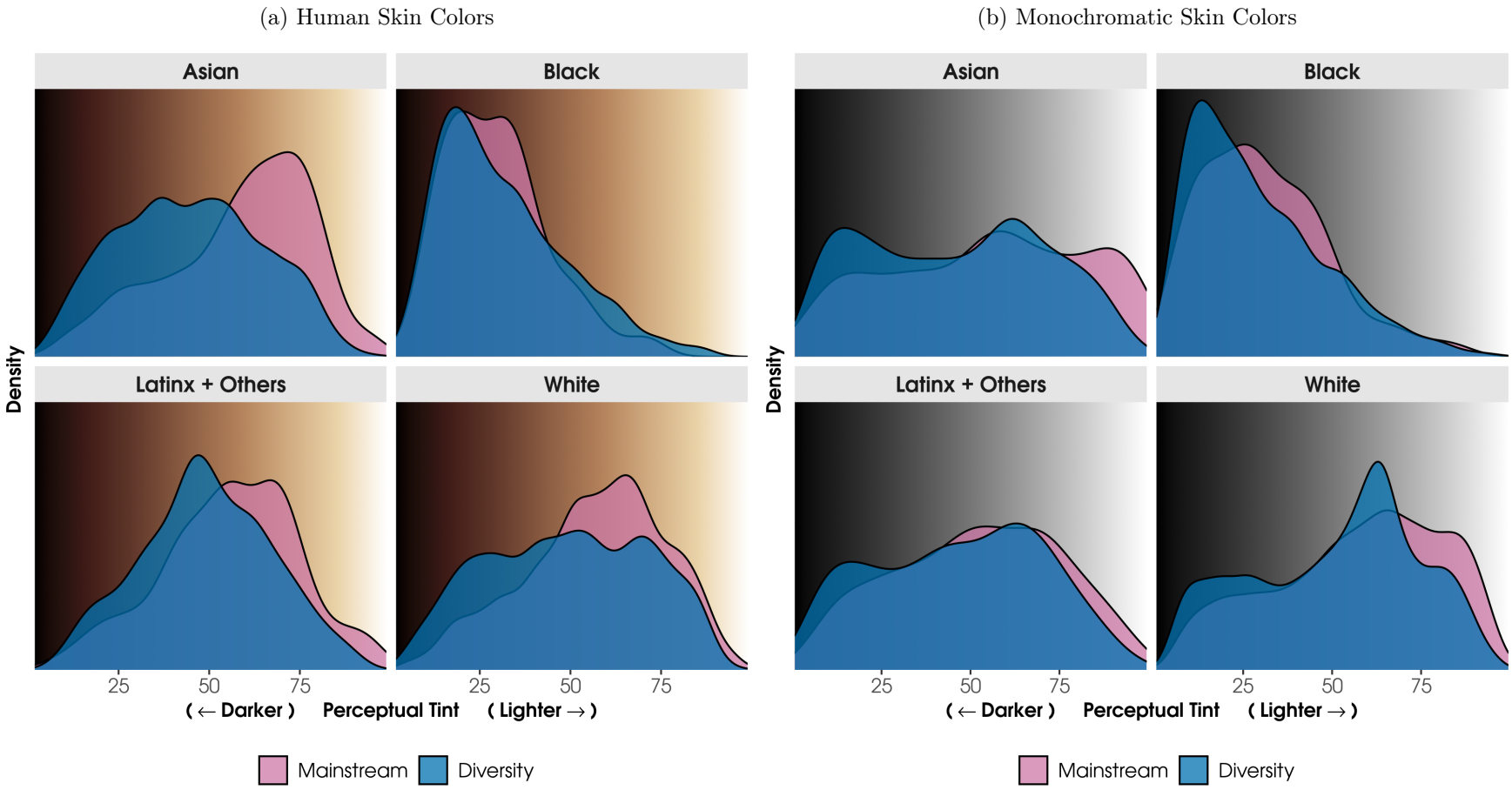


(c) Mean Proportion in Each Tercile, All Collections



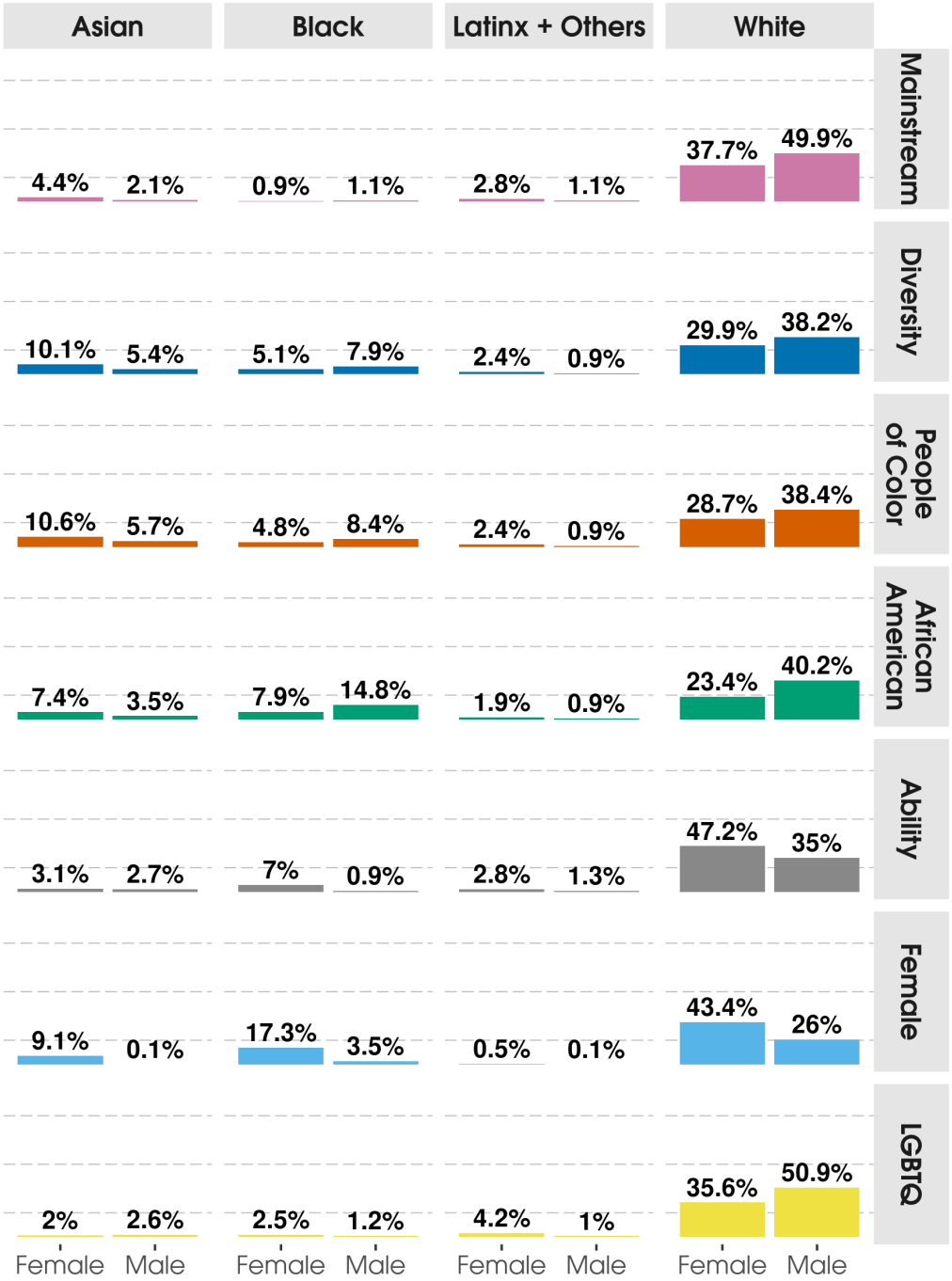
Note: This figure shows our analysis of the representative skin colors of the individual faces we detect in the images found in the books we analyze, focusing on monochromatic faces. Panel A shows the distribution of skin color tint for faces detected in books from the Mainstream and Diversity collections. 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 III.

Figure 7. Skin Color by Predicted Race of Pictured Characters



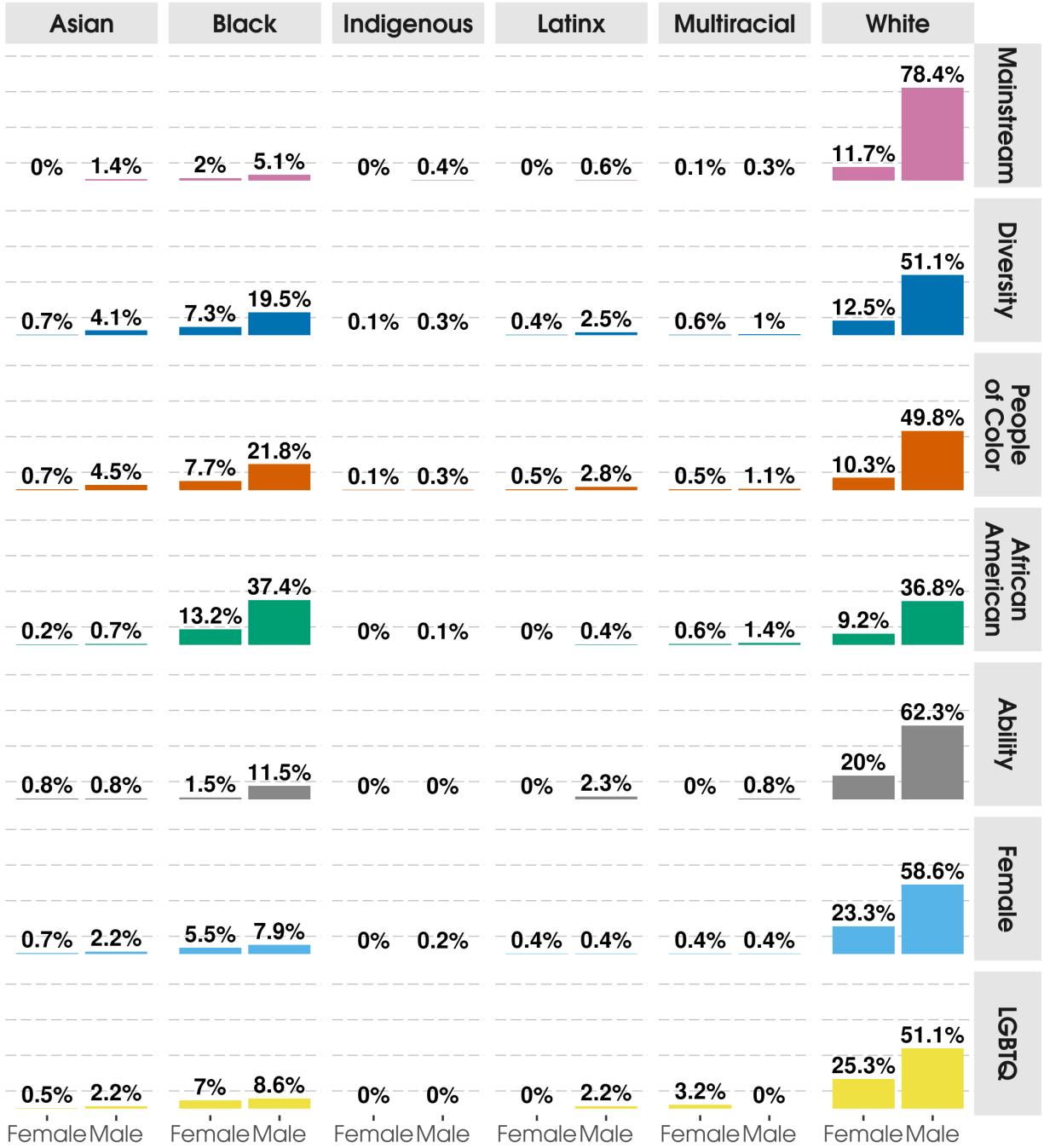
Note: This figure shows the distribution of skin color tint by predicted race of the detected faces in the Mainstream and Diversity collections. Skin tint is determined by the L* value of a face's representative skin color in L*a*b* space. We extract a face's representative skin color using methods described in Section III.B.2. Skin color tint distribution for non-typical skin colors not shown. Race was classified by our trained AutoML model as described in Section III.C.

Figure 8. Race and Gender Predictions of Pictured Characters



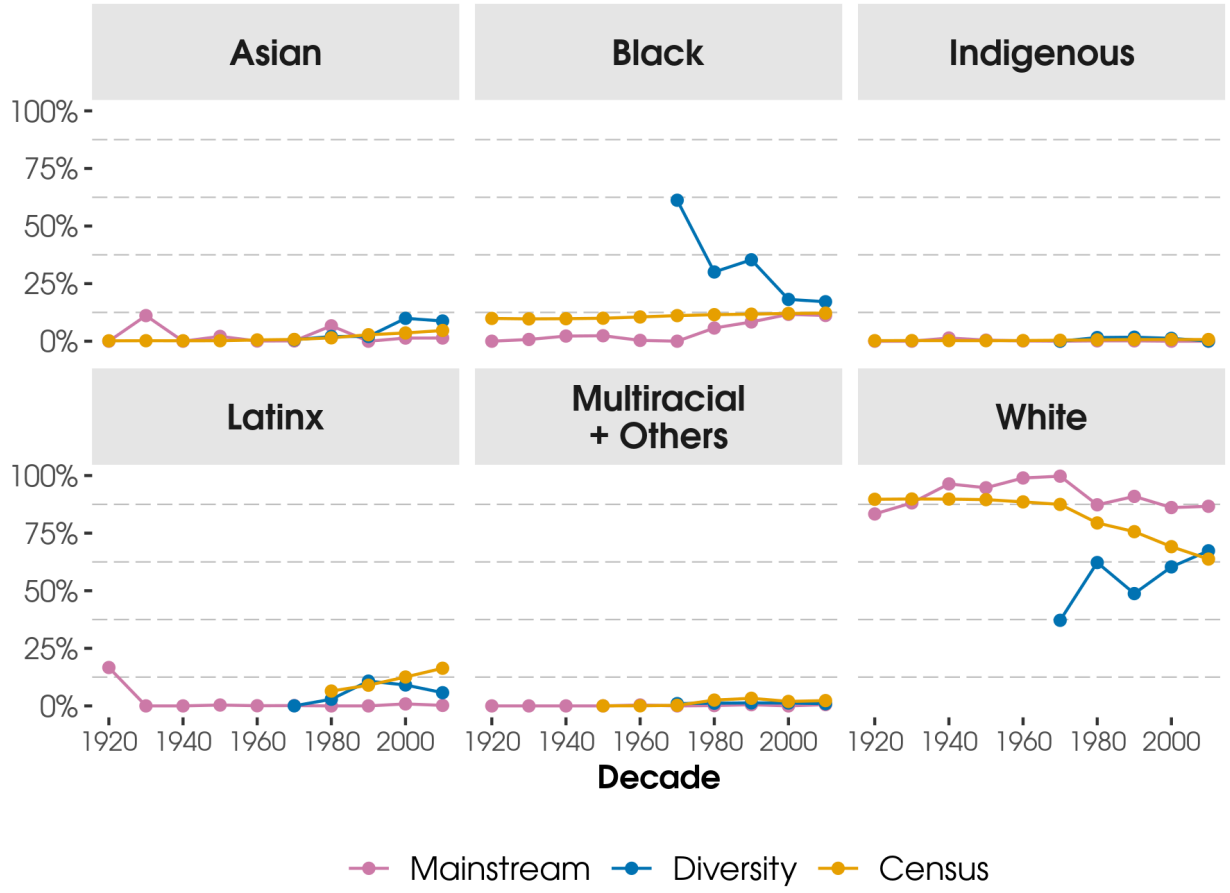
Note: In this figure, we show the proportion of detected faces in all collections by race and gender predictions. Race and gender were classified by our trained AutoML model as described in Section III.C.

Figure 9. Race and Gender Classifications of Famous Figures in the Text



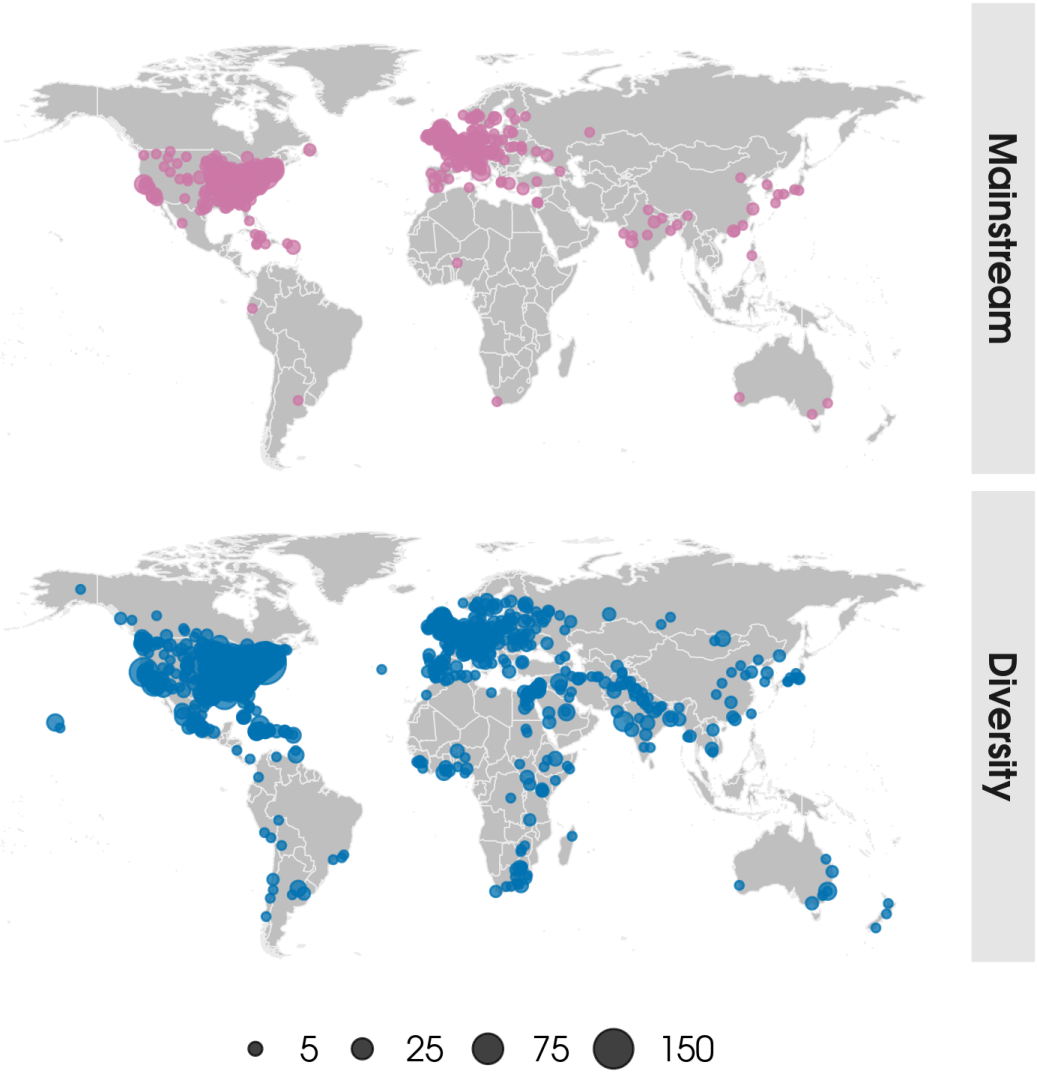
Note: In this figure, we count the number of famous people mentioned at least once in a given book and sum over all books in a collection. We then show the percentage breakdown of these famous people by race and gender. For example, if Aretha Franklin was mentioned at least once in two separate books 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.1. 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.

Figure 10. Share of US Population and Famous People in the Text, by Race/Ethnicity



Note: In this figure, we show the percent of famous people in the Mainstream and Diversity collections by predicted race and the share of the US population by race/ethnicity. To do this, we count the number of famous people mentioned at least once in a given book and sum over all books in a collection by decade. 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. As described in Section IV.B.1, we classify famous people using a two step-process. We manually label the race of famous people. 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. We describe how we process the US Census Data in Section V.B.

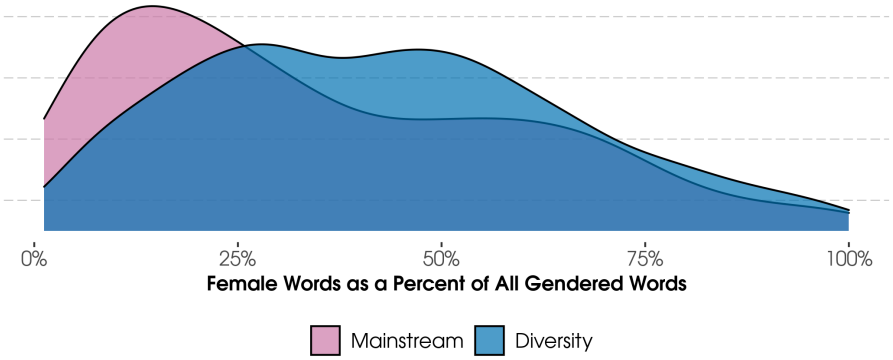
Figure 11. Birthplace of Famous Figures



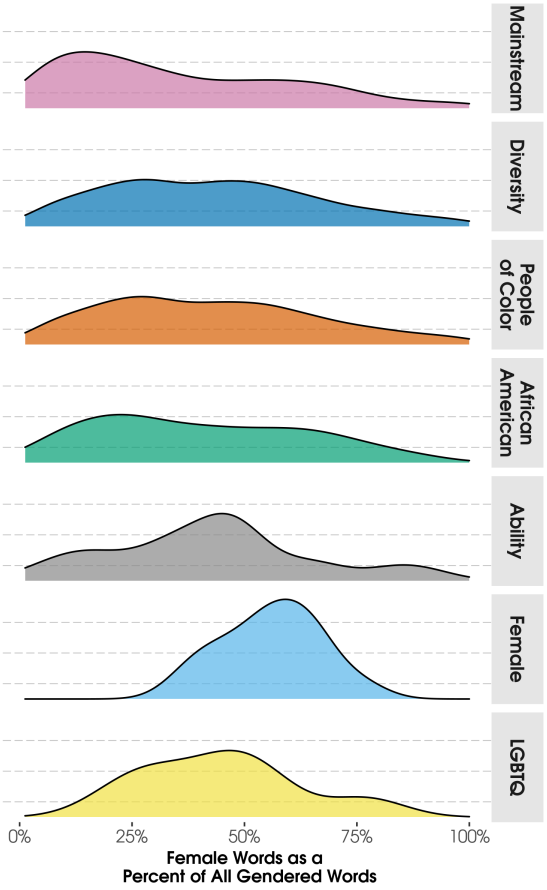
Note: In this figure, we show two maps in which we plot the distribution of the place of birth of the famous people in our books: one for the Mainstream collection and one for the Diversity collection. We identify birthplace using a model trained on text from Wikipedia biographies collected by Pantheon (Yu et al., 2016). If the city/town they were born in was unavailable, we use birth country. Size of dots correspond to the number of famous characters born in a given location that are mentioned at least once in a given book and then aggregated across all books in a collection. 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.

Figure 12. Distribution of Female Words, by Collection

(a) Mainstream vs. Diversity Collections



(b) All Collections

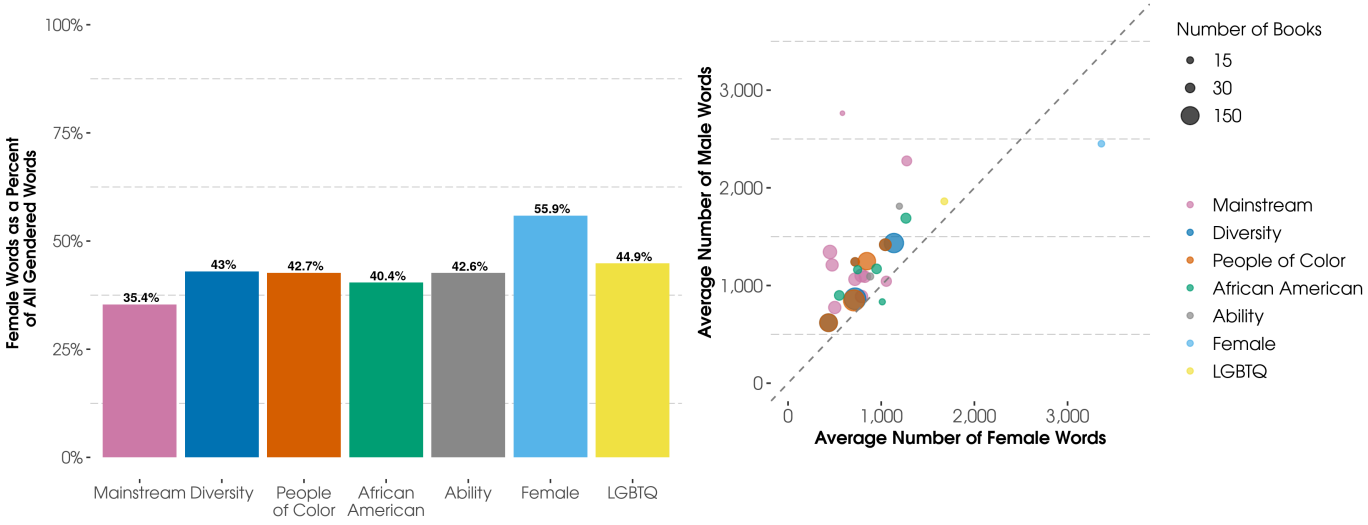


Note: In this figure we show the distribution of all female gendered words as a proportion of all gendered words per book, over all books in a collection. Panel A shows this for the Mainstream and Diversity collections; Panel B shows this for Mainstream collection, Diversity collection, and the separate collections which comprise the Diversity collection. In this case, gendered words encompass the total number of gendered first names, gender predictions of famous characters, gendered pronouns, and a pre-specified list of other gendered tokens (e.g., queen, nephew). We list the pre-specified gendered tokens in the Data Appendix.

Figure 13. Female Words as a Percent of All Gendered Words

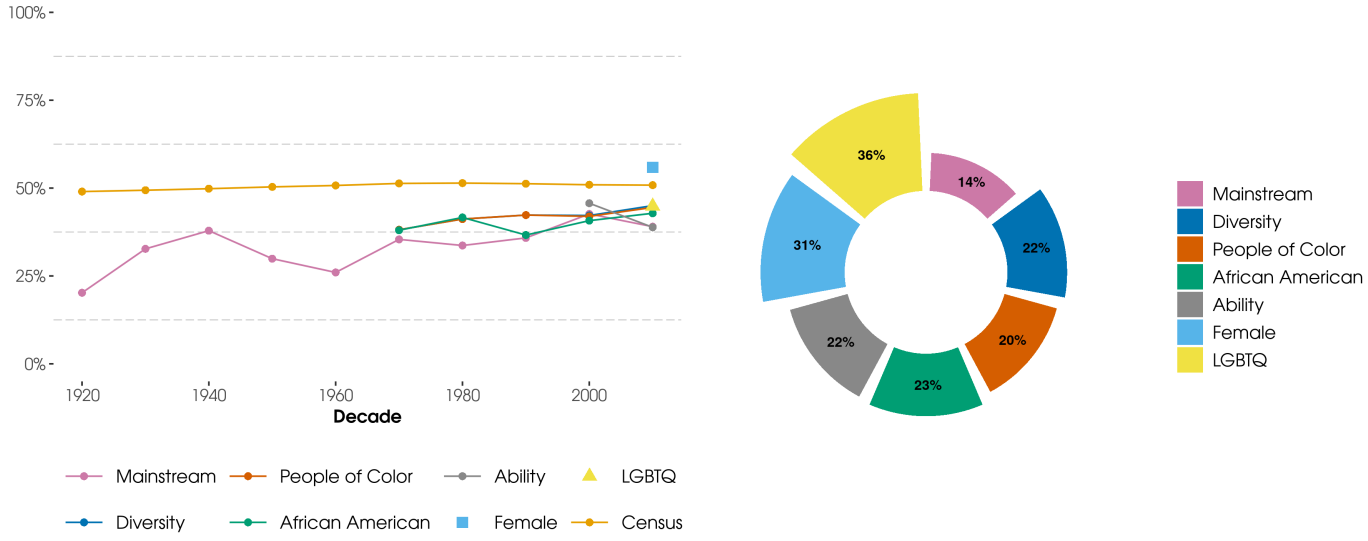
(a) Percent Female Words

(b) Male Words vs. Female Words



(c) Female Words & US Population Share

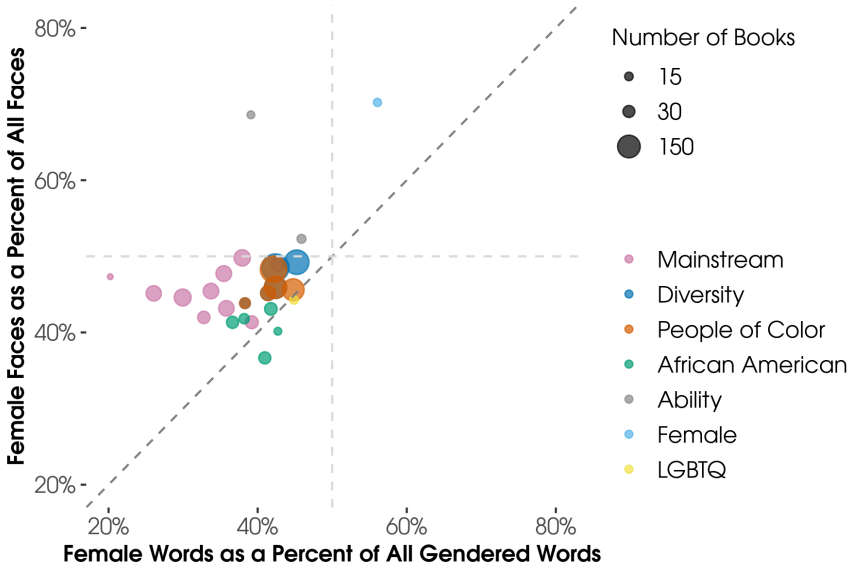
(d) Percent Famous Females



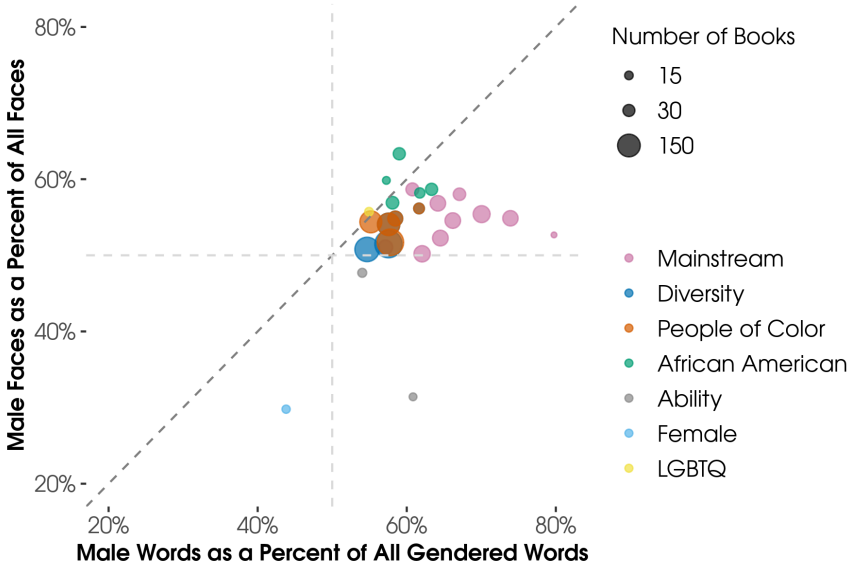
Note: In this figure, we show four different analyses of gendered words. Panel A shows the proportion of gendered words that are female in each collection. Panel B shows how this value varies by decade. Panel C shows the number of female words vs. the number of male words by collection and decade book averages. In this case, gendered words encompass the total number of gendered first names, gender predictions of famous characters, gendered pronouns, and a pre-specified list of other gendered tokens (e.g., queen, nephew). We list the pre-specified gendered tokens in the Data Appendix. In Panel D, 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 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.

Figure 14. Women Should be Seen More Than Heard?

(a) Percent Female Faces vs. Words



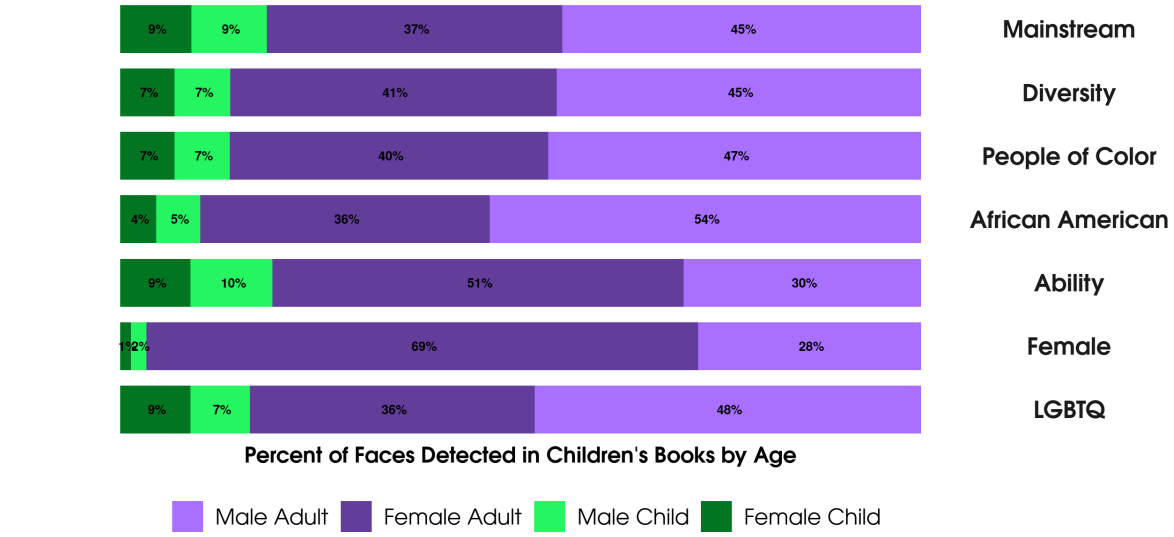
(b) Percent Male Faces vs. Words



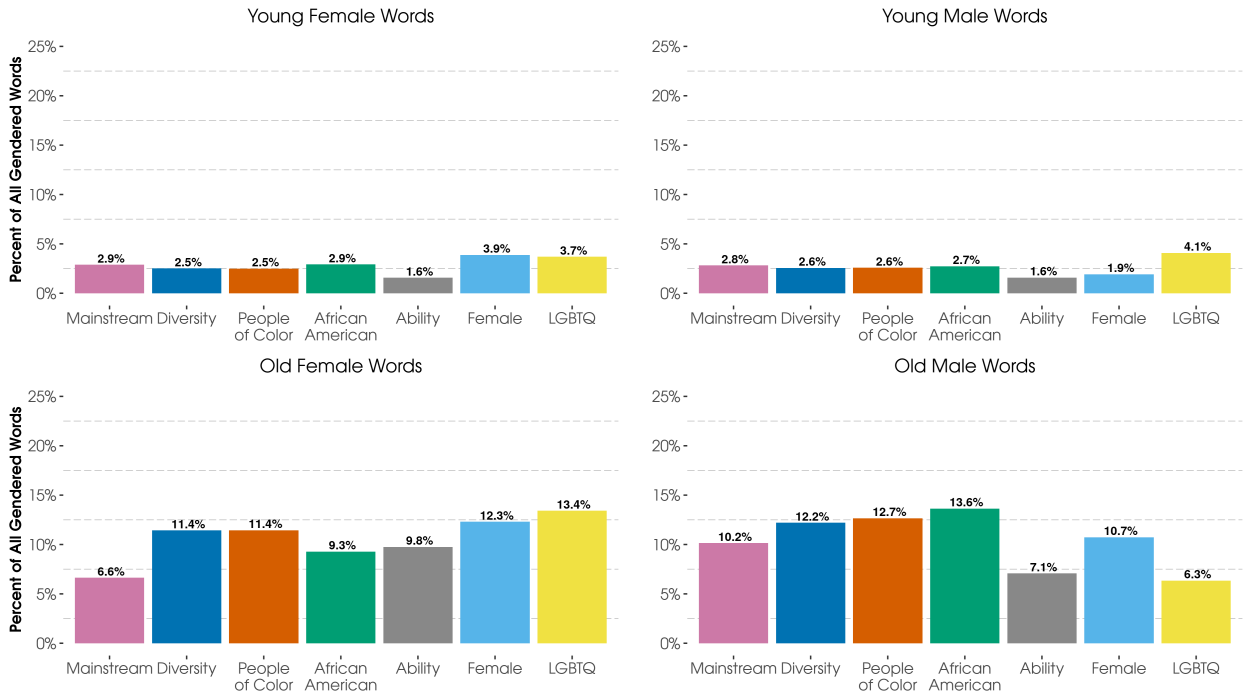
Note: In this figure, we contrast the proportion of females (and males) represented in the text with the proportion of of females (and males) represented in the images of the books in our data. In Panel A, we plot collection-by-decade averages of female representation in images (on the y-axis) and female representation in text (on the x-axis). In Panel B, for illustrative purposes, we plot the analogous collection-by-decade averages of male representation, which are the converse of the patterns shown in Panel A.

Figure 15. More Adults than Children in Images and Text

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



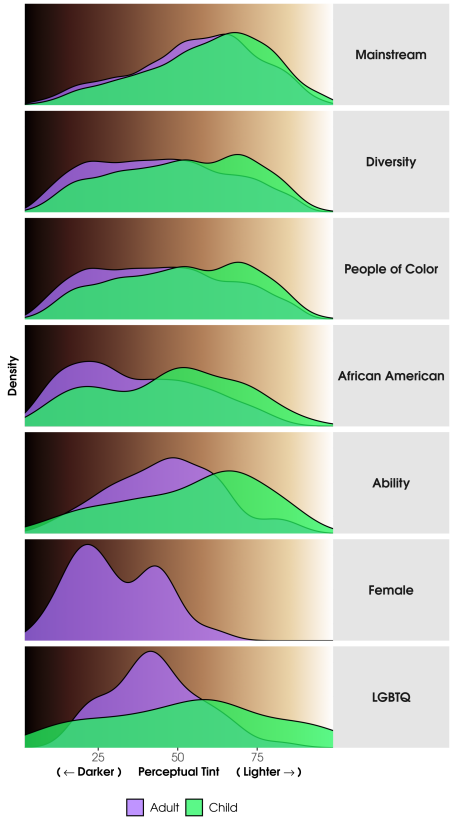
(b) Percent of Gendered Words by Age Group



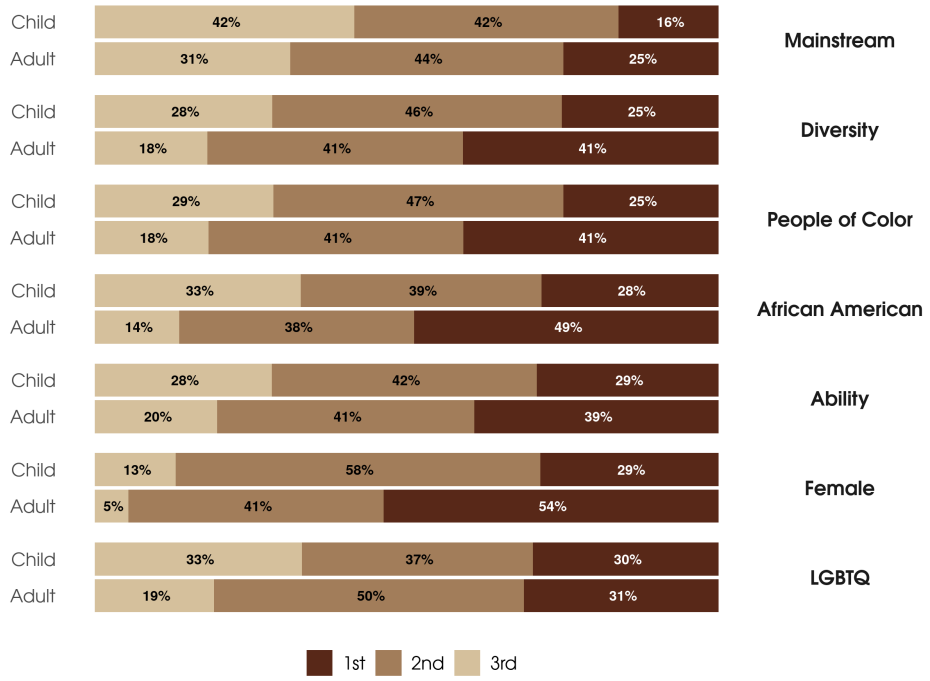
Note: In this figure, we show analysis of the representation of age and gender. In Panel A, we show analysis of predicted age and gender in the faces in images. Specifically, we plot the proportion of identified faces classified in each age (adult vs. child) and gender (female vs. male) category. In Panel B, we show analysis of age and gender in text. Specifically, we plot the proportion of words that refer to specific gender-age combinations (e.g., female adults or male children) as a percent of all gendered words in the book. Gendered words encompass the total number of gendered first names, gender predictions of famous characters, gendered pronouns, and a pre-specified list of other gendered tokens (e.g., queen, nephew). We list the pre-specified gendered tokens in the Data Appendix.

Figure 16. Children Are Consistently Depicted with Lighter Skin than Adults

(a) Skin Color Distribution by Age



(b) Proportion of Faces in Skin Color Terciles, by Age



Note: In this figure, we show analysis of how the representation of skin color varies with the predicted age of the person being represented. In Panel A, we show the distribution of skin tint values of representative skin color of detected faces in the Mainstream and Diversity collections by the classified age (adult vs. child) of the face. In Panel B, 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) described in Section III.A. Within these faces, we classify age and gender 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. We extract a face's representative skin color using methods described in Section III.B.2. These figures show the results for images that have identified human skin colors (polychromatic skin colors where $R \geq G \geq B$).

Appendices

A.1 Appendix Tables

Table A1. Top Five Most Mentioned Famous People, by Collection

Collection	Rank	Name	Race	Gender	Mentions	Books
Mainstream	1	George Washington	White	Male	148	32
Mainstream	2	Abraham Lincoln	White	Male	195	25
Mainstream	3	Thomas Jefferson	White	Male	72	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	423	68
Diversity	2	Abraham Lincoln	White	Male	67	40
Diversity	3	George Washington	White	Male	62	40
Diversity	4	Frederick Douglass	Black	Male	129	30
Diversity	5	Langston Hughes	Black	Male	109	30
People of Color	1	Martin Luther King Junior	Black	Male	406	64
People of Color	2	Abraham Lincoln	White	Male	65	38
People of Color	3	George Washington	White	Male	58	37
People of Color	4	Frederick Douglass	Black	Male	129	30
People of Color	5	Langston Hughes	Black	Male	108	29
African American	1	Martin Luther King Junior	Black	Male	239	26
African American	2	Langston Hughes	Black	Male	53	17
African American	3	Malcolm X	Black	Male	70	12
African American	4	Frederick Douglass	Black	Male	43	12
African American	5	Rosa Parks	Black	Female	44	11
Ability	1	Harold Pinter	White	Male	79	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	Martin Luther King Junior	Black	Male	17	4
Female	2	John F. Kennedy	White	Male	8	4
Female	3	Jimmy Carter	White	Male	15	3
Female	4	Betty Friedan	White	Female	10	3
Female	5	Richard Nixon	White	Male	9	3
LGBTQ	1	Alicia Keys	Multiracial	Female	3	3
LGBTQ	2	Britney Spears	White	Female	3	3
LGBTQ	3	Marilyn Monroe	White	Female	3	3
LGBTQ	4	Julia Roberts	White	Female	5	2
LGBTQ	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 A2. 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	158	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	Emily Dickinson	White	24	14
People of Color	1	Rosa Parks	Black	153	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	22	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	11	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
LGBTQ	1	Alicia Keys	Multiracial	3	3
LGBTQ	2	Britney Spears	White	3	3
LGBTQ	3	Marilyn Monroe	White	3	3
LGBTQ	4	Julia Roberts	White	5	2
LGBTQ	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 A3. Top Five Most Mentioned Famous Males, by Collection

Collection	Rank	Name	Race	Mentions	Books
Mainstream	1	George Washington	White	148	32
Mainstream	2	Abraham Lincoln	White	195	25
Mainstream	3	Thomas Jefferson	White	72	15
Mainstream	4	John Adams	White	60	14
Mainstream	5	Benjamin Franklin	White	23	12
Diversity	1	Martin Luther King Junior	Black	423	68
Diversity	2	Abraham Lincoln	White	67	40
Diversity	3	George Washington	White	62	40
Diversity	4	Frederick Douglass	Black	129	30
Diversity	5	Langston Hughes	Black	109	30
People of Color	1	Martin Luther King Junior	Black	406	64
People of Color	2	Abraham Lincoln	White	65	38
People of Color	3	George Washington	White	58	37
People of Color	4	Frederick Douglass	Black	129	30
People of Color	5	Langston Hughes	Black	108	29
African American	1	Martin Luther King Junior	Black	239	26
African American	2	Langston Hughes	Black	53	17
African American	3	Malcolm X	Black	70	12
African American	4	Frederick Douglass	Black	43	12
African American	5	Duke Ellington	Black	22	11
Ability	1	Harold Pinter	White	79	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	Martin Luther King Junior	Black	17	4
Female	2	John F. Kennedy	White	8	4
Female	3	Jimmy Carter	White	15	3
Female	4	Richard Nixon	White	9	3
Female	5	Barack Obama	Black	5	3
LGBTQ	1	Alexander Hamilton	White	4	2
LGBTQ	2	Adam Lambert	White	3	2
LGBTQ	3	Alice Cooper	White	3	2
LGBTQ	4	Michael Jackson	Black	3	2
LGBTQ	5	Andy Warhol	White	2	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.

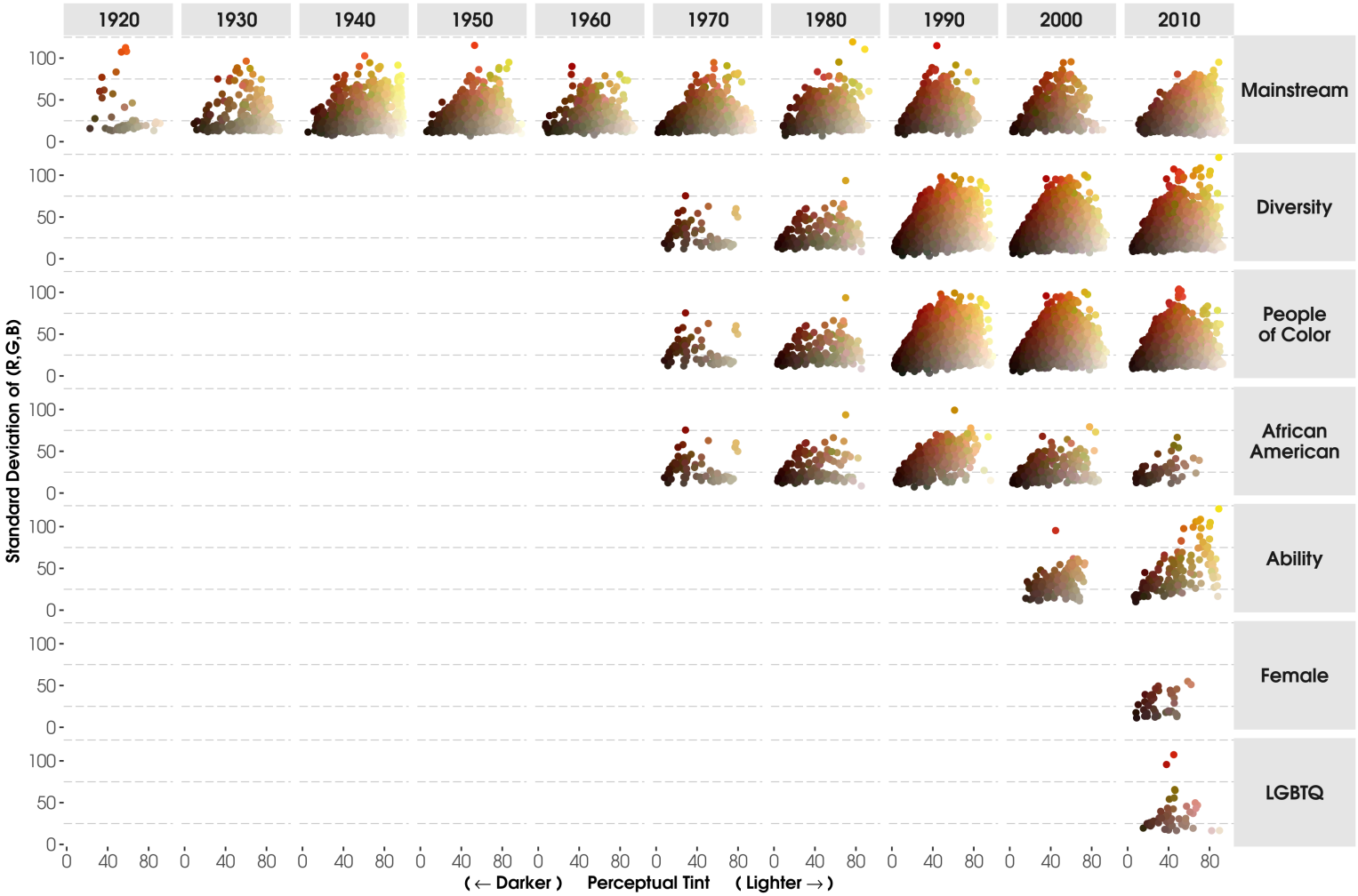
Table A4. Top Mentioned Famous Person, by Collection and Decade

Decade	Mainstream	Diversity	People of Color	African American	Ability	Female	LGBTQ
1920	James Fenimore Cooper *White Male* Charles Darwin *White Male* Mark Twain *White Male*						
1930	Abraham Lincoln *White Male*						
1940	Benjamin Franklin *White Male*						
1950	George Washington *White Male*						
1960	George Washington *White Male*						
1970	Claude Lorrain *White Male* Leonardo da Vinci *White Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*			
1980	George Washington *White Male*	Franklin D. Roosevelt *White Male*	Franklin D. Roosevelt *White Male*	Paul Robeson *Black Male*			
1990	William Shakespeare *White Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*			
2000	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *White Male*	Martin Luther King Jr. *Black Male*	Langston Hughes *Black Male*	Judy Blume *White Female*		
2010	George Washington *White Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*	Martin Luther King Jr. *Black Male*	Andy Warhol *White Male*	Martin Luther King Jr. *White Male*	Alicia Keys *Multiracial Female* Marilyn Monroe *White Female* Britney Spears *White Female*

Note: In this table, we show the top most uniquely mentioned 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 mentioned famous person in that collection-by-decade.

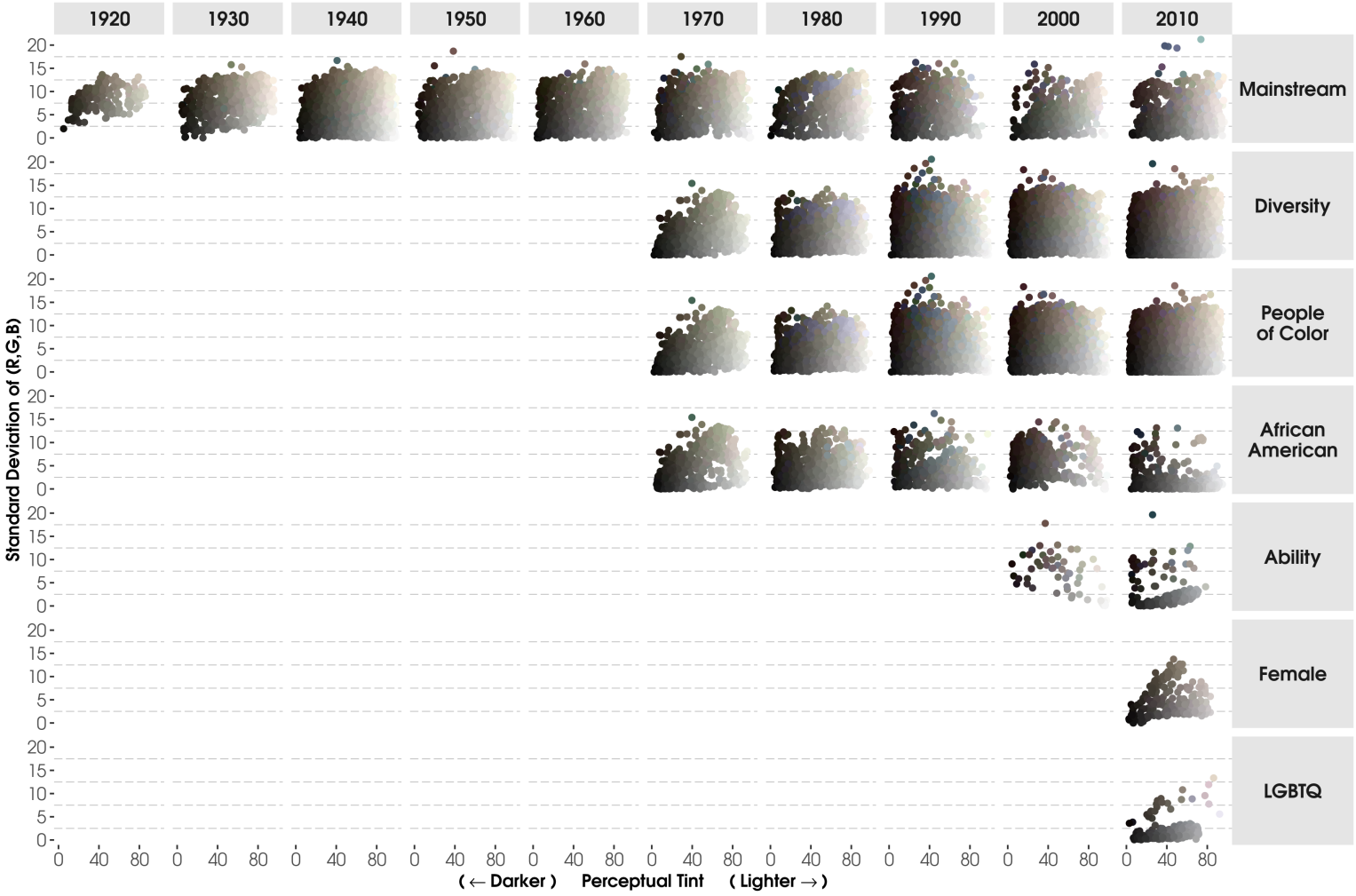
B.2 Appendix Figures

Figure A1. Skin Color Data Over Time, Human Skin Colors



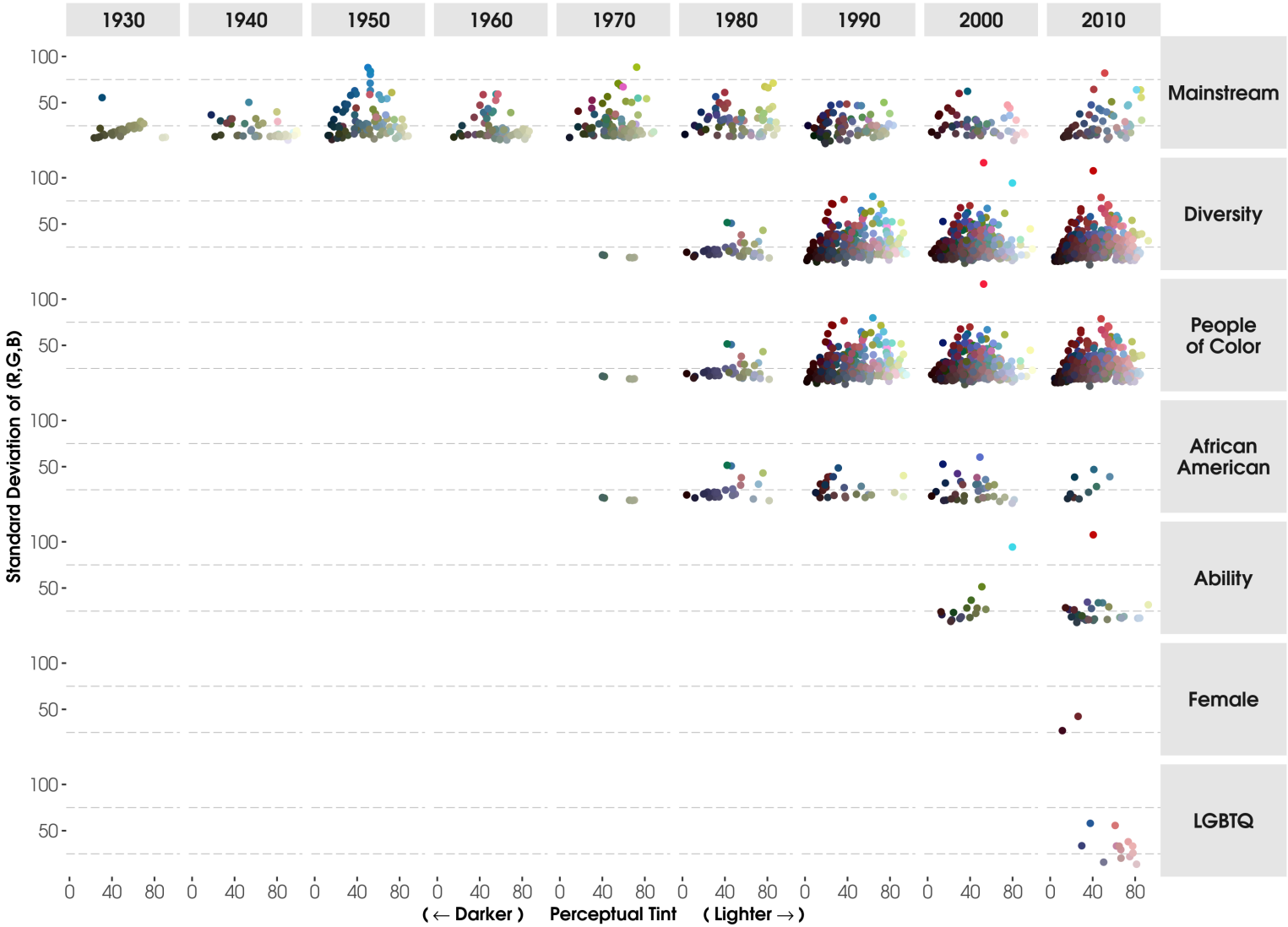
Note: In this figure, we show the representative skin colors for all detected faces with human skin colors (polychromatic skin colors where R $\geq$ G $\geq$ B) in each collection-by-decade. As described in Section III, we use our face detection model (FDAI) trained on illustrations to classify faces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

Figure A2. Skin Color Data Over Time, Monochromatic Skin Colors



Note: In this figure, we show the representative skin colors for all detected faces with monochromatic skin colors (e.g., black and white) in each collection-by-decade. As described in Section III, 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 III.B.2.

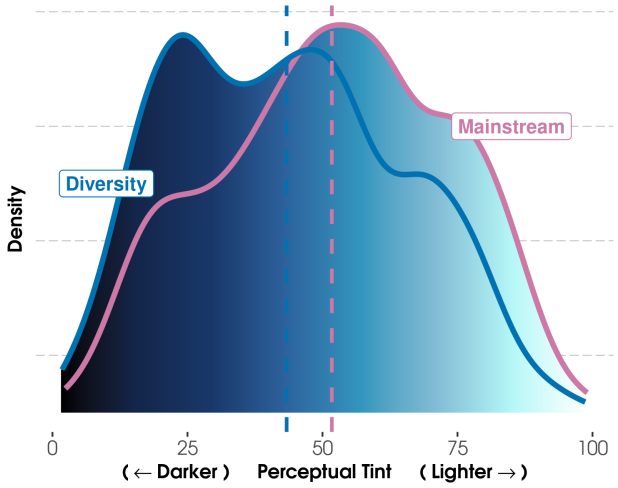
Figure A3. Skin Color Data Over Time, Polychromatic Non-Typical Skin Colors



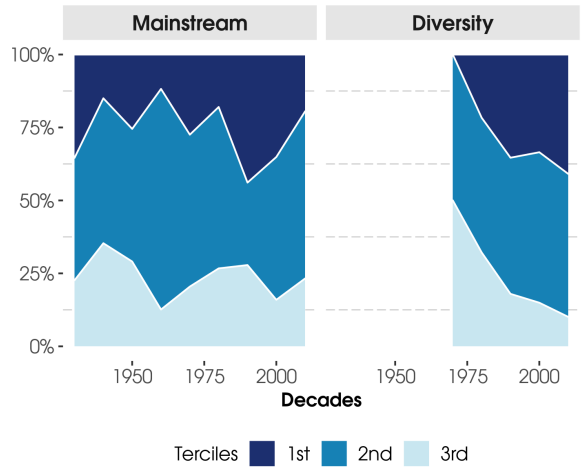
Note: In this figure, we show the representative skin colors for all detected faces with non-typical skin colors in each collection-by-decade. As described in Section III, we use our face detection model (FDAI) trained on illustrations to classify faces in images. We determine a face's representative skin color using methods described in Section III.B.2. The data shown in this figure begin in the 1930s, as opposed to in the 1920s as in Figures A1 and A2, because we detect no faces with polychromatic non-typical skin colors in books from the 1920s.

Figure A4. Skin Colors in Faces, by Collection: Polychromatic Non-Typical Skin Colors

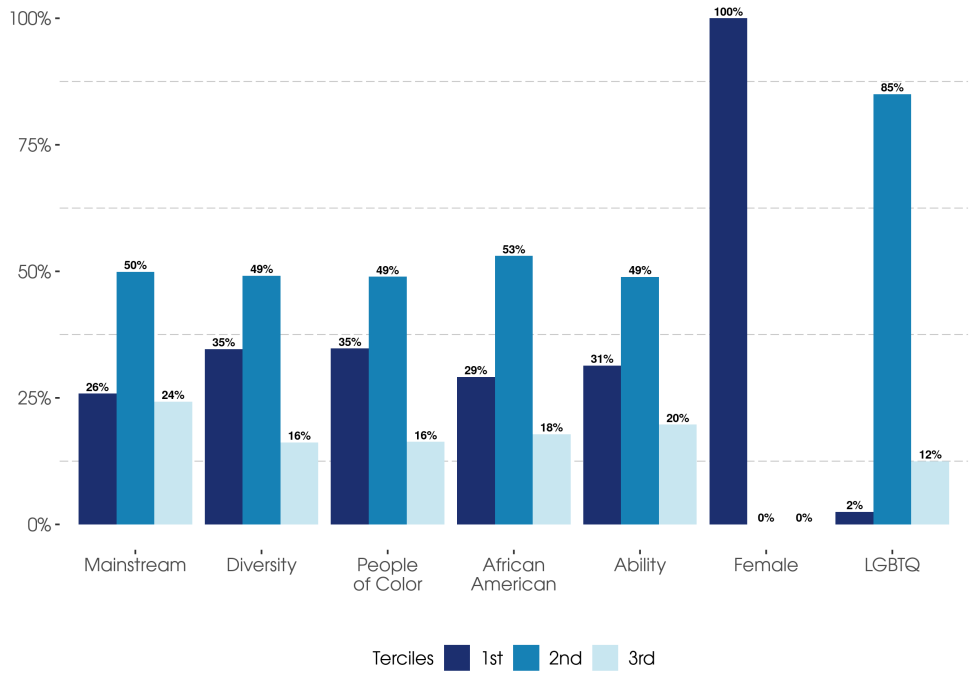
(a) Distribution of Skin Colors



(b) Mean Proportion in Each Tercile, Over Time

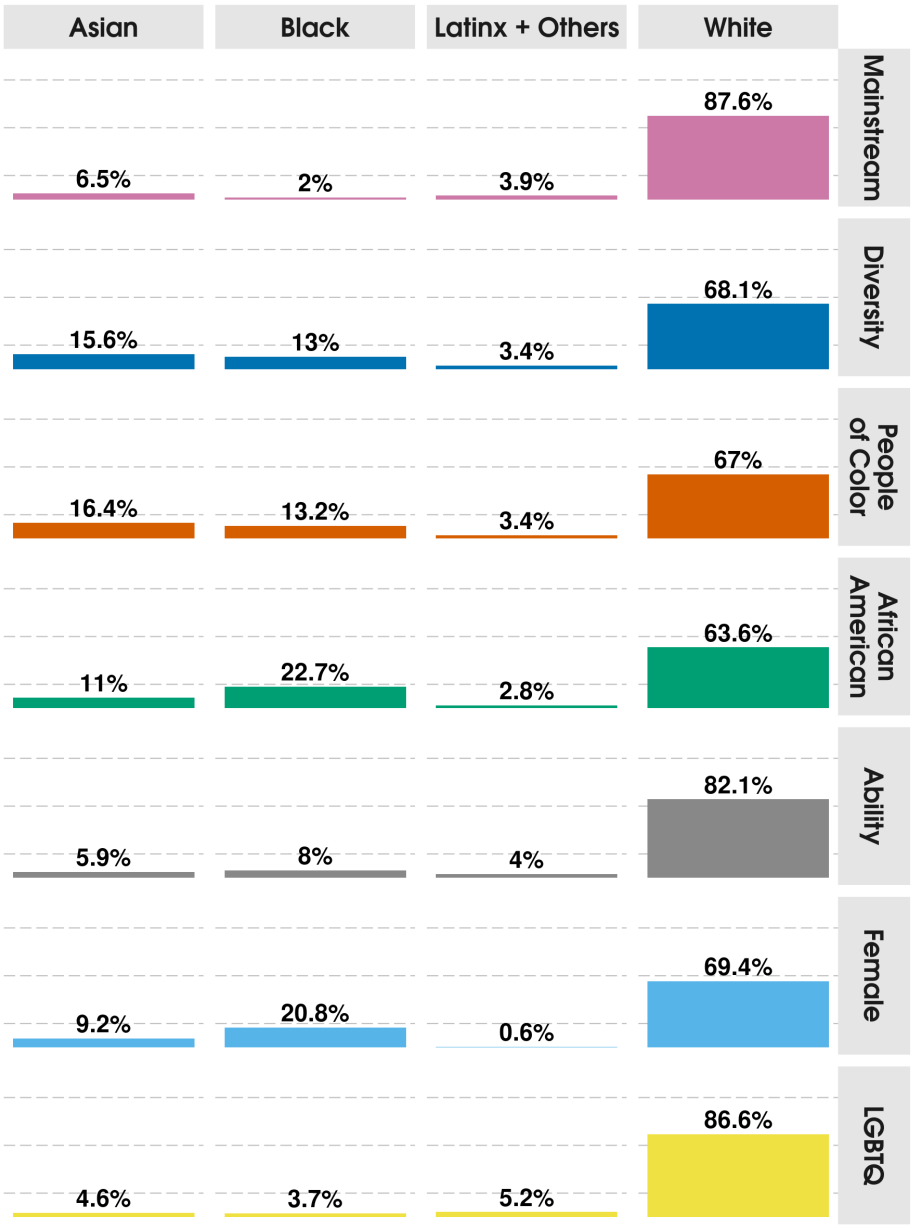


(c) Mean Proportion in Each Tercile, All Collections



Note: This figure shows our analysis of the representative skin colors of the faces detected in the books we analyze, focusing 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 III.

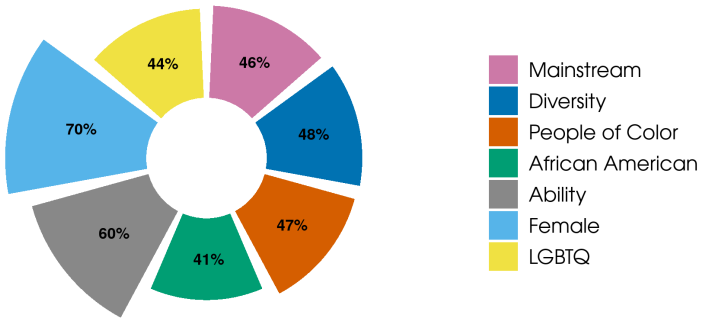
Figure A5. Most Pictured Characters Are Classified as White



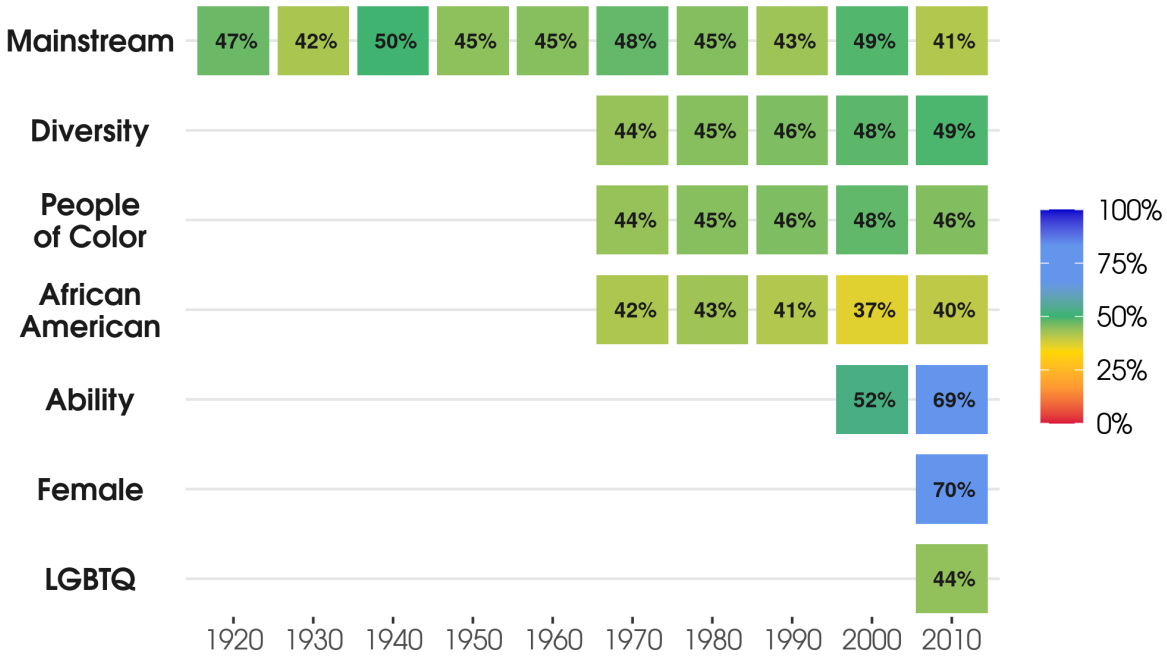
Note: In this figure, we show our main analysis of predicted race of pictured faces in images, reporting the proportion of faces in images which our model labels as a given race. We detect faces using our face detection model (FDAI) described in Section III.A. Within these faces, we classify age and gender using an AutoML algorithm we trained using the UTKFace public data set.

Figure A6. Proportion of Detected Faces Which Are Female-Presenting

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



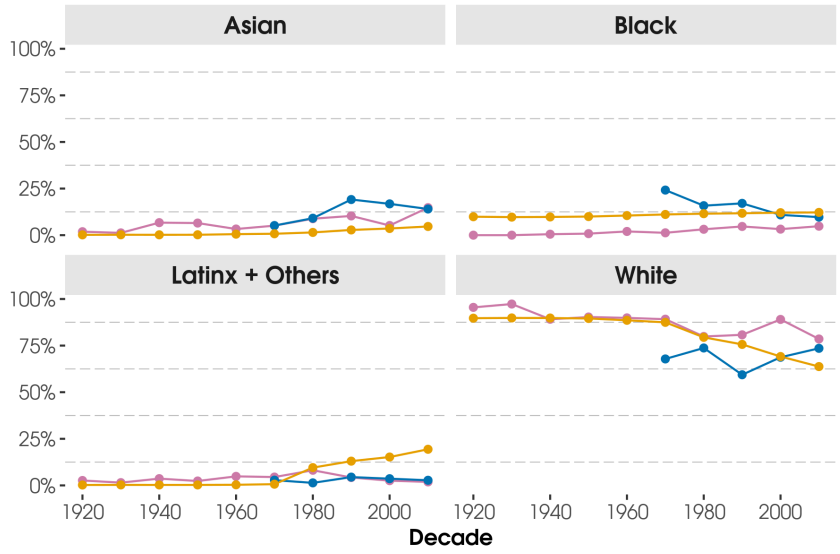
(b) Percent of Female-Presenting Faces Detected, Over Time



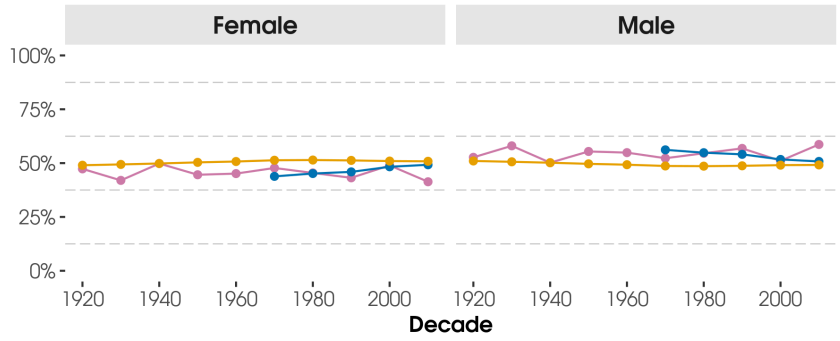
Note: In this figure, we show our main analysis of gender in images, reporting the proportion of faces in images which our model labels as female. In Panel A, we show collection-level estimates of the percent of detected faces classified as female. In Panel B, we show these values over time.

Figure A7. Share of US Population and Pictured Characters, by Identity

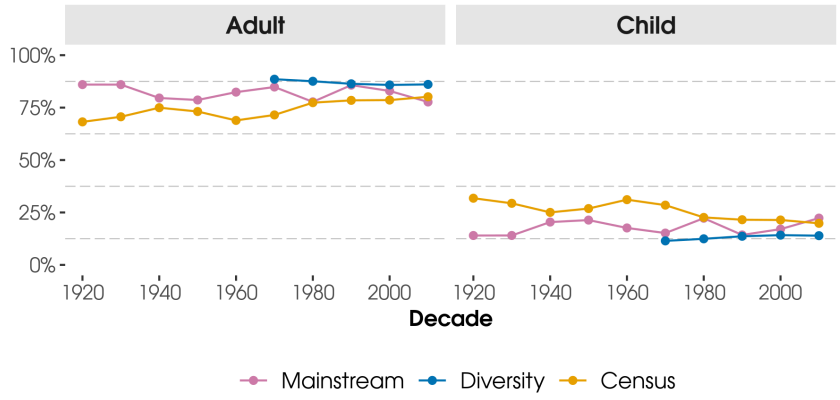
(a) Race/Ethnicity



(b) Gender



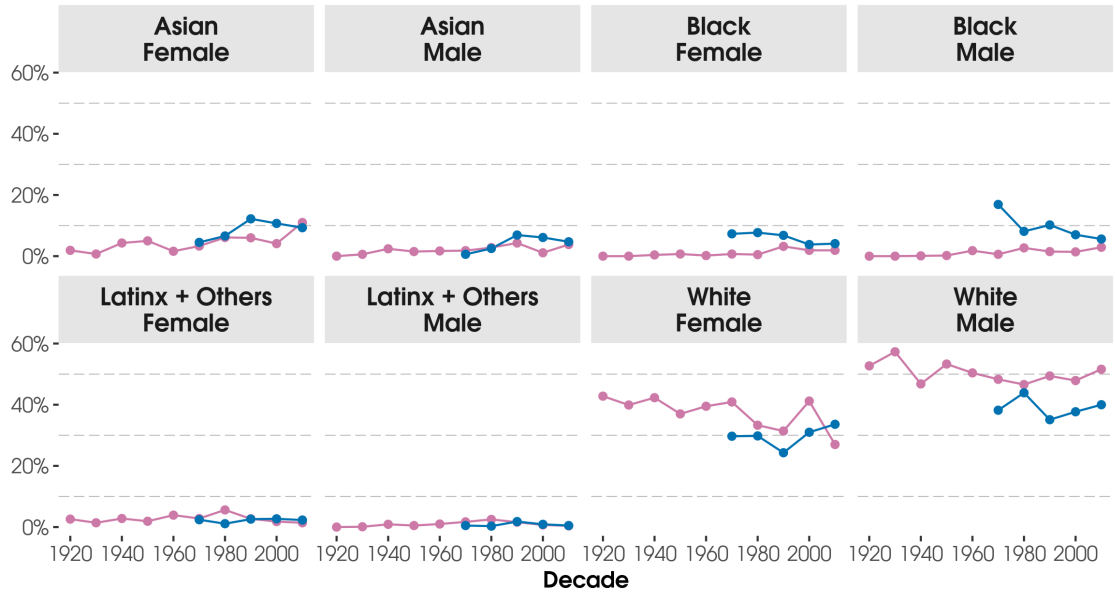
(c) Age



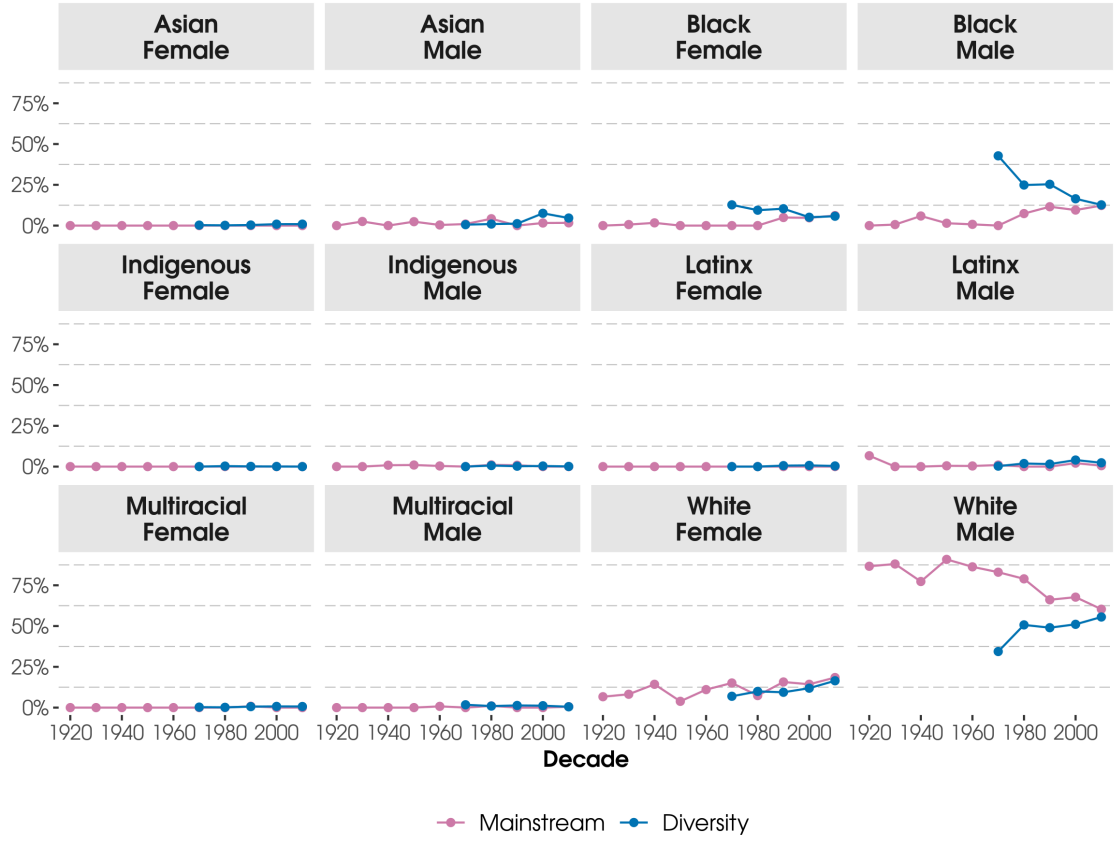
Note: We show the share of the US population of specific identities mapped on the share of the pictured characters classified as a given identity over time. In Panel A, we show this by race/ethnicity. Each race/ethnicity category is constructed to be mutually exclusive as defined in Section V.B. In Panel B, we show this by gender. In Panel C, we show this by age group.

Figure A8. Proportion of Characters in Images and Text, by Race and Gender

(a) Detected Faces (Images)



(b) Famous Figures (Text)

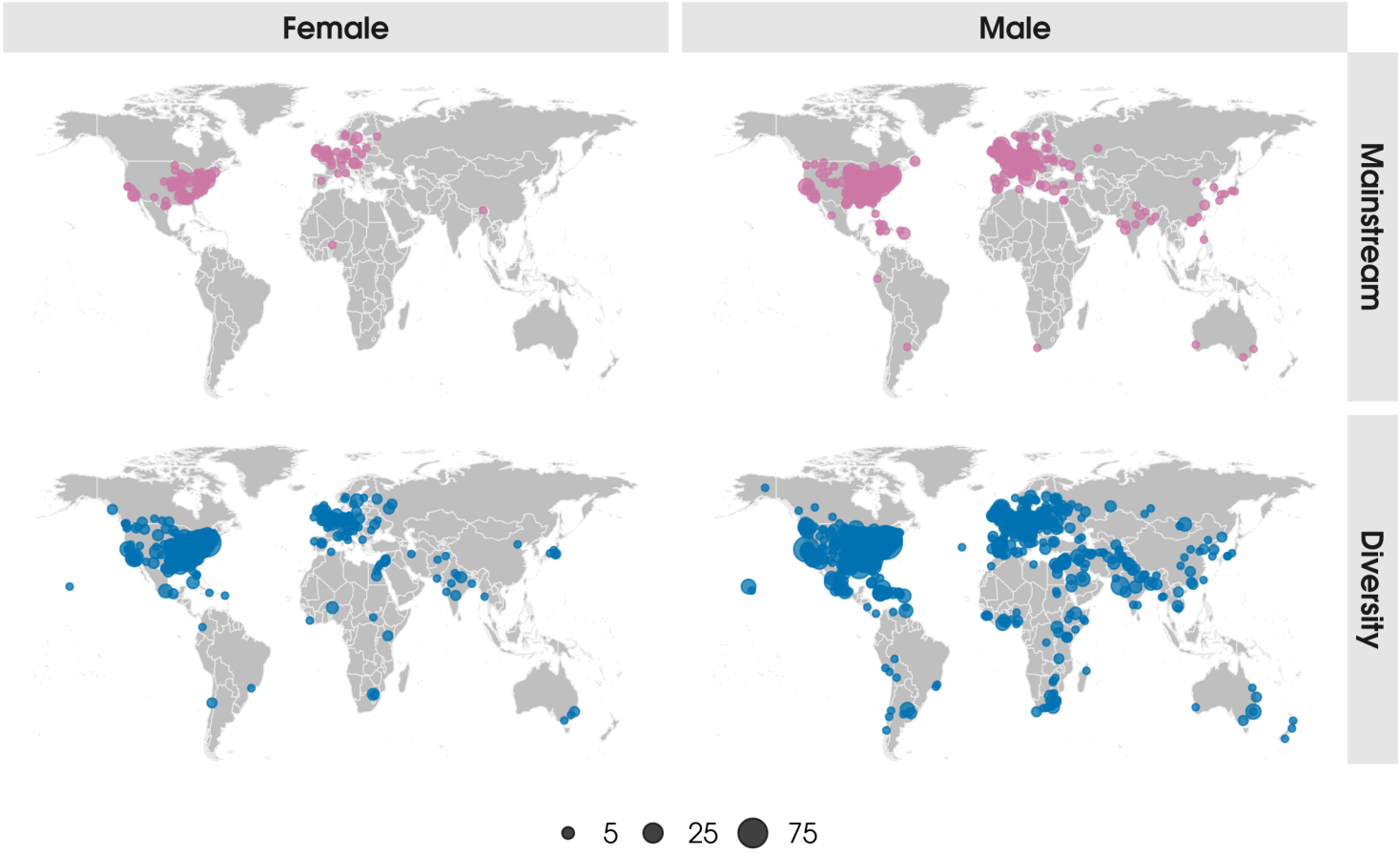


Note: In this figure, we show the share of the characters by race and gender over time. In Panel A, we show this for detected faces in images. In Panel B, we show this for famous figures mentioned in the text.

Figure A9. Race of Famous People in the Text

Note: In this figure, we show a separate measure of the representation of race in text: the proportion of famous people of different racial identities. To do this, 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 show these proportions for each collection, classified into six racial categories defined on the x-axis. We identify famous individuals using methods described in Section IV.B.1. We manually label the race of famous people. 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.

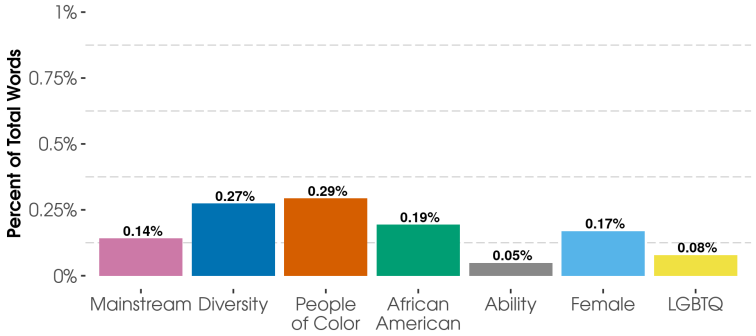
Figure A10. Birthplace of Famous Figures, by Gender



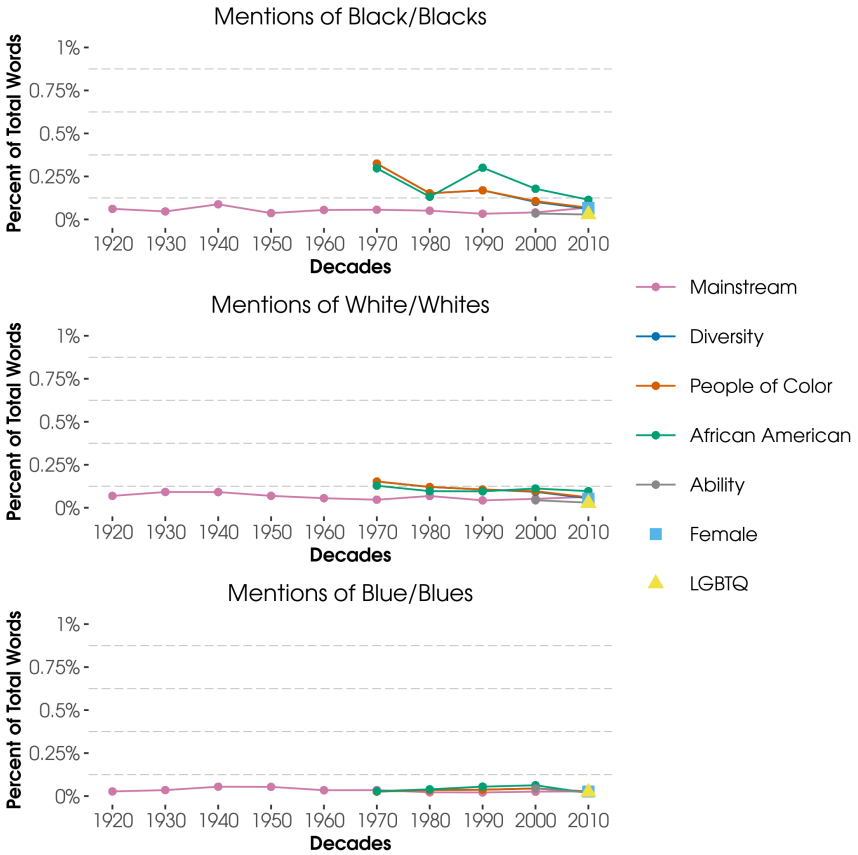
Note: In this figure, we show collection-specific measures of the birthplace of famous figures, separately for females and males. We identify famous individuals as well as their gender and birthplace using methods described in Section IV.B.1. If the city/town they were born in was unavailable, we use birth country. Size of dots correspond to the number of famous characters born in a given location that are mentioned at least once in a given book and then aggregated across all books in a collection. 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.

Figure A11. Token-Based Proxies for Race: Nationality and Color

(a) Words Related to Nationality



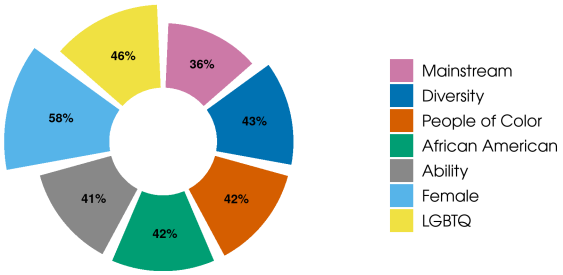
(b) Color Words



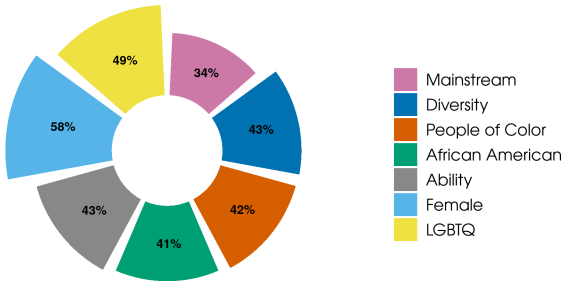
Note: In this figure, we show two measures of the representation of race in text: words related to nationalities and words related to color. In Panel A, we show collection-specific averages of the proportion of words in a book that relate to nationalities. In Panel B, we show collection-by-time averages of mentions of three color words: black, white, and blue – as a proportion of all words in our data. We generated the estimates using a pre-specified list of words (also known as "tokens," as described in Section IV.A). We provide this list in the Data Appendix.

Figure A12. Female Representation in Text, by Type of Word

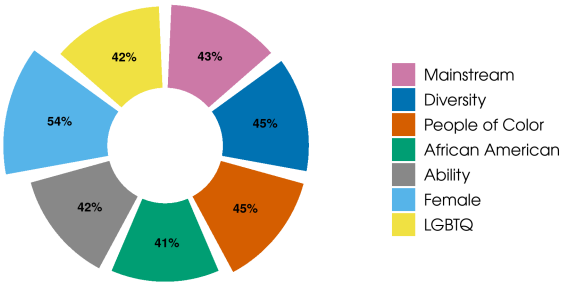
(a) Pronouns



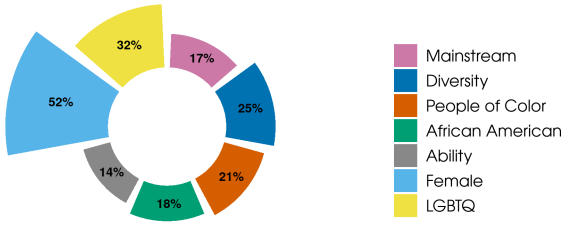
(b) Specific Tokens



(c) Character First Names

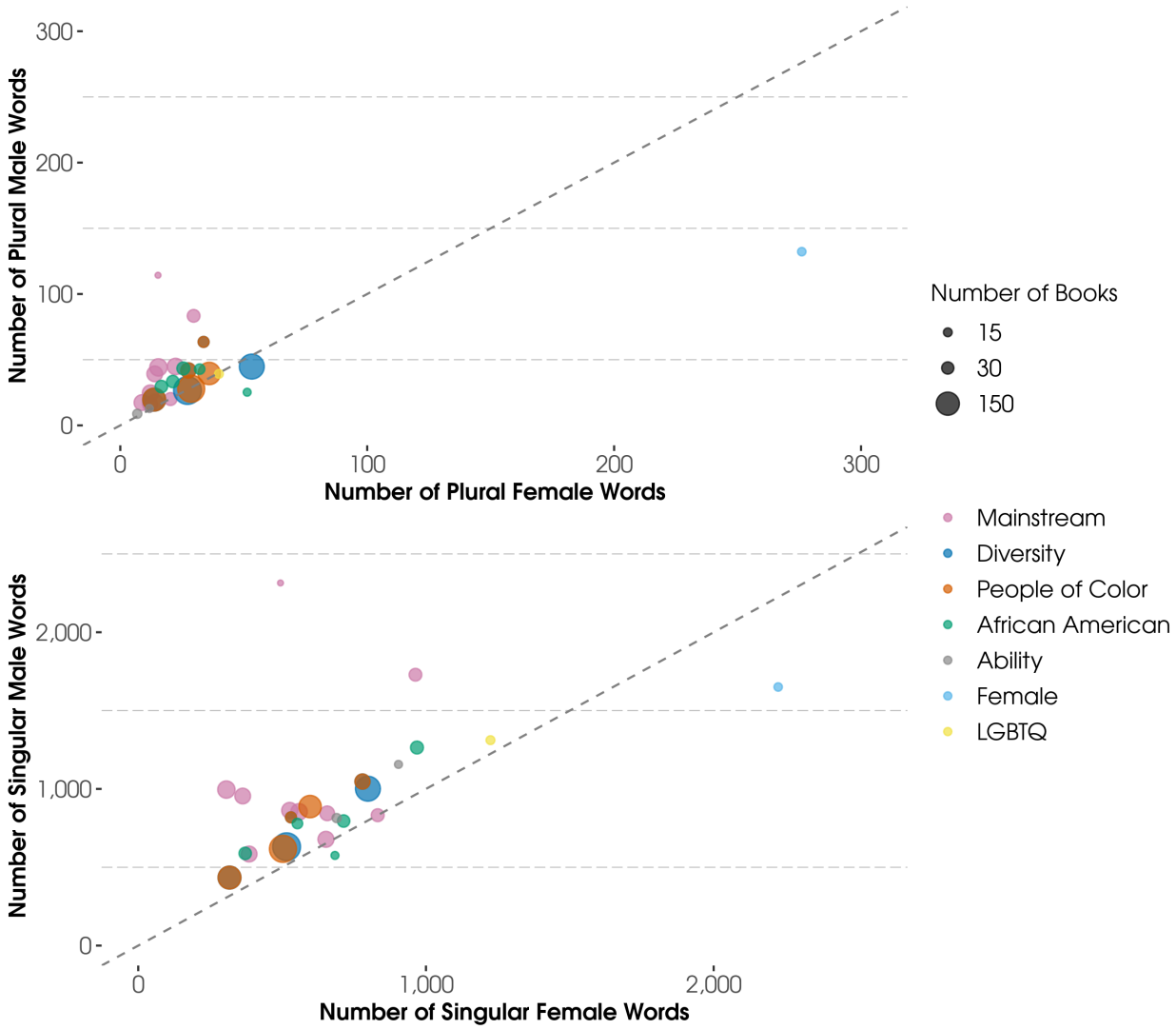


(d) Famous Figures



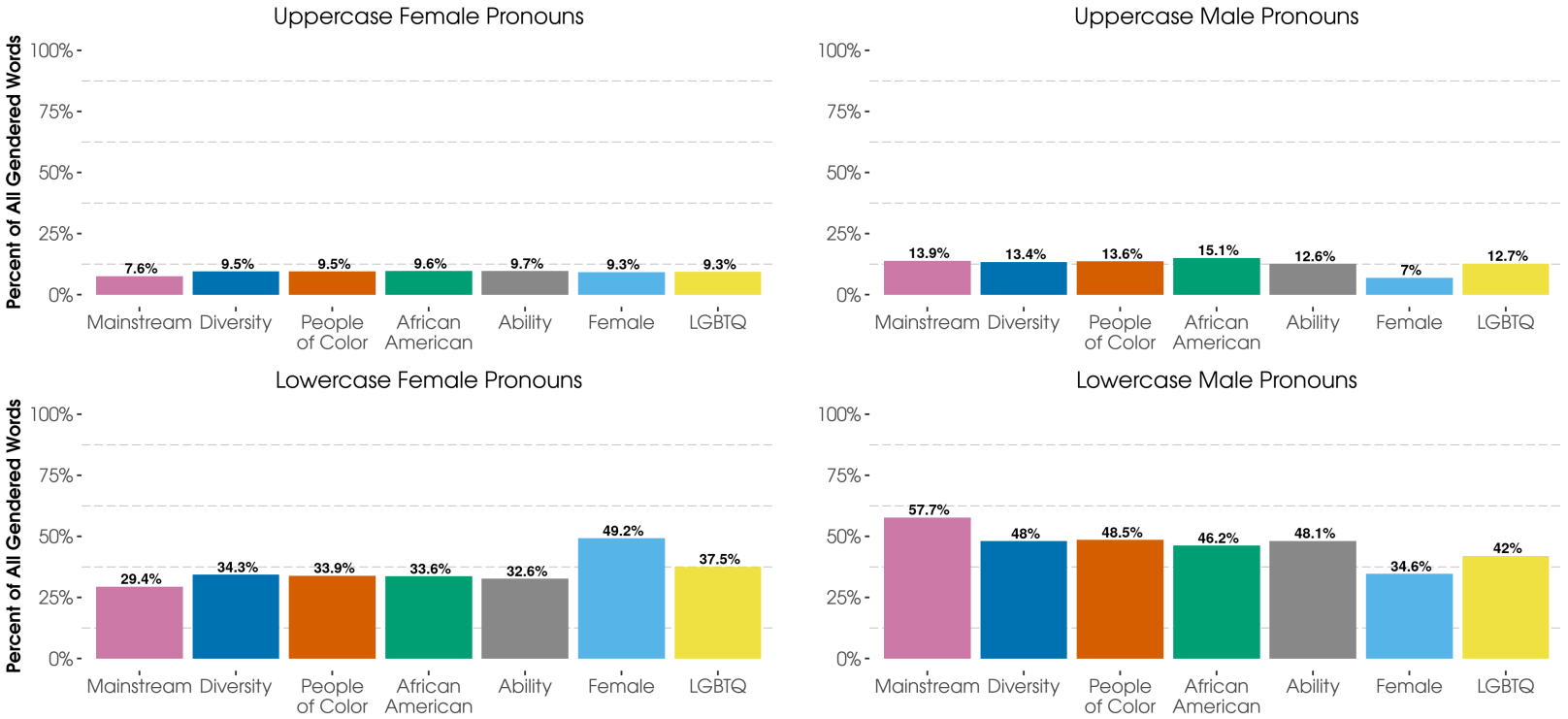
Note: In this figure, we show the proportion of female words out of all gendered words, across collections, separately by category of word. In Panel A, we show the percentage of gendered pronouns which are female. In Panel B, we show the percentage of words from a pre-specified list of female gendered words (tokens) such as queen or niece (full list provided in Data Appendix). In Panel C, we show the percentage of character first names that are predicted to be female based on Social Security Administration data. In Panel D, we count each time a famous person is mentioned across all books in a collection and show the percentage breakdown of these famous people by gender. For example, if Aretha Franklin was mentioned 5 times in one book and 10 times in another book within the Diversity collection, we would count her as appearing 15 times for that collection.

Figure A13. Gender Representation, by Quantity of Individuals



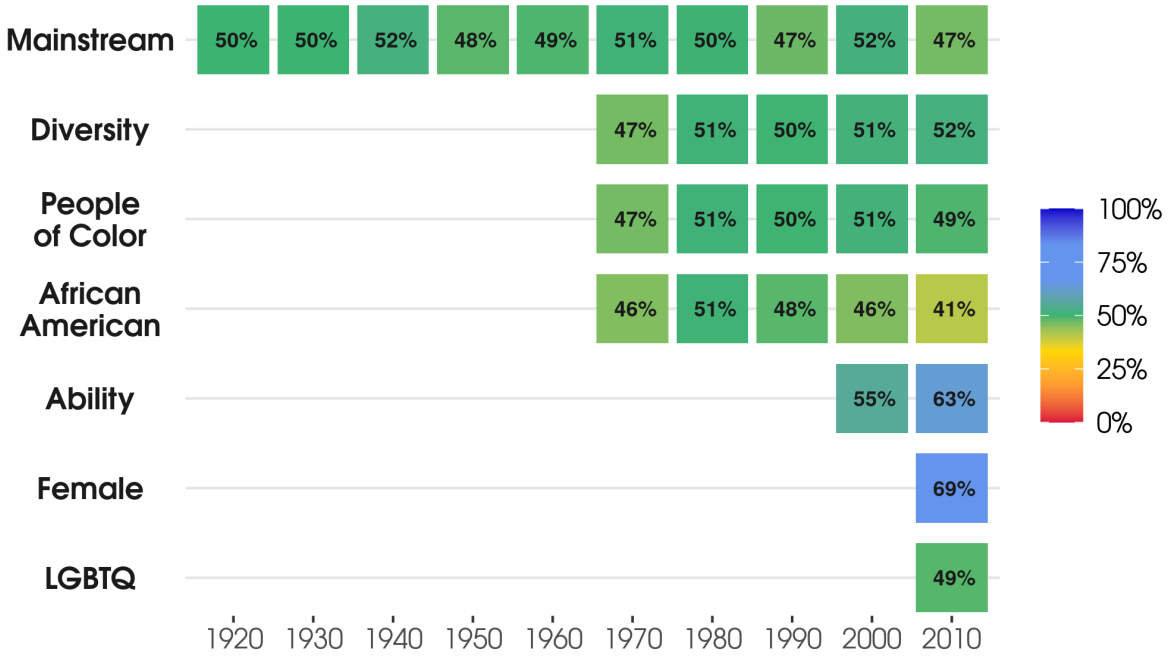
Note: In this figure, we show how gender representation in text varies by whether it is referring to an individual or a group of people; in other words, whether the representation of gender varies by presence of singular (individuals) or plural (groups of people) gendered words. We show collection-specific averages by decade. In the top plot, we show the number of plural male words vs. the number of plural female words; in the bottom plot, we show the number of singular male words vs. the number of singular female words. These male and female words were drawn from a pre-specified list of other gendered tokens (e.g., queen, nephew). We list the pre-specified gendered tokens in the Data Appendix.

Figure A14. Proportion of Females and Males Serving as Subjects and Objects of Sentences



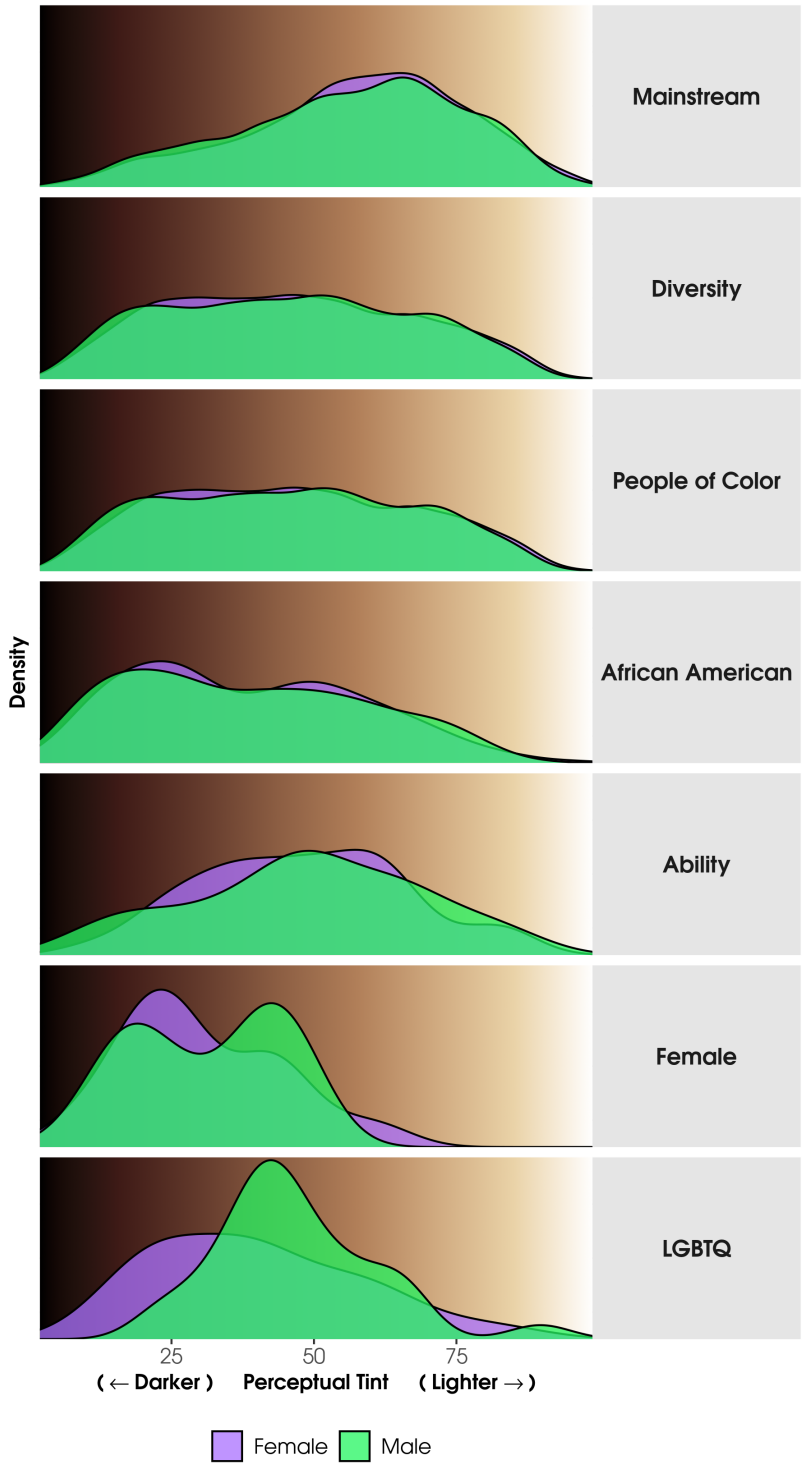
Note: In this figure, we plot the representation of gender by its location in sentences. The top two plots show the average proportion of all gendered pronouns in a book that are uppercase, and the bottom two plots show those that are lowercase. The left plots show the female-related pronouns, and the right plots show the male-related pronouns. We present these separately because an uppercase pronoun is more likely than a lowercase pronoun to be the subject, as opposed to the object, of the sentence in which it appears.

Figure A15. Average Probability a Face is Female, by Decade and Collection



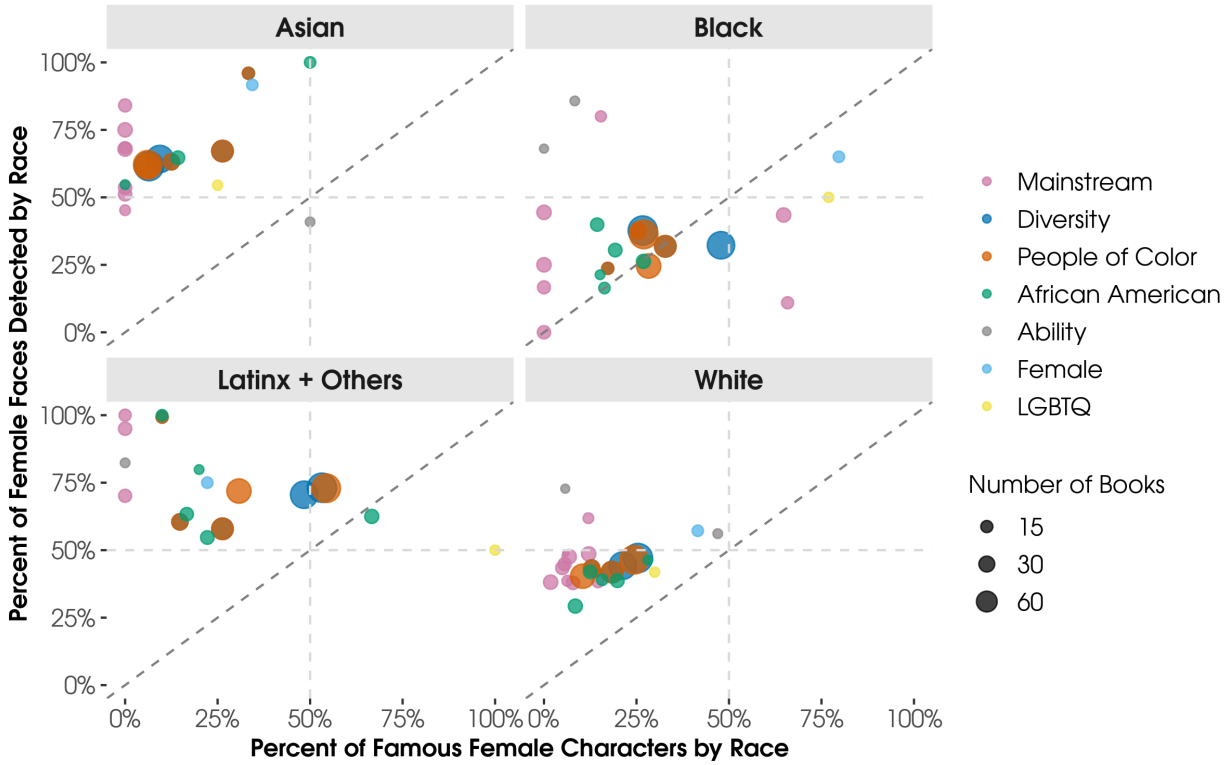
Note: In this figure, we present the average probability that a face was classified as being female in a given collection by decade. We classify gender using an AutoML algorithm trained on the UTKFace public data set.

Figure A16. Distribution of Skin Color, by Gender and Collection



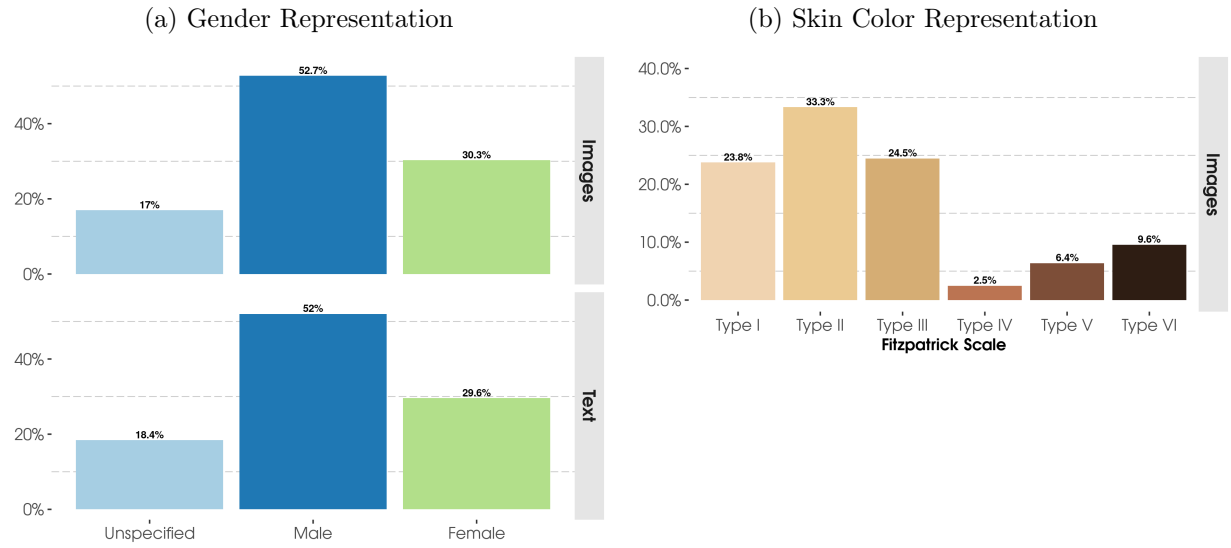
Note: In this figure, we show the distribution of skin tint by gender in detected faces with human skin color (polychromatic skin colors where R $\geq$ G $\geq$ B) for each collection of books. Skin tint is determined by the L* value of a face's representative skin color in L*a*b* space. We extract a face's representative skin color using methods described in Section III.B.2.

Figure A17. Race and Gender Representation in Images and Text



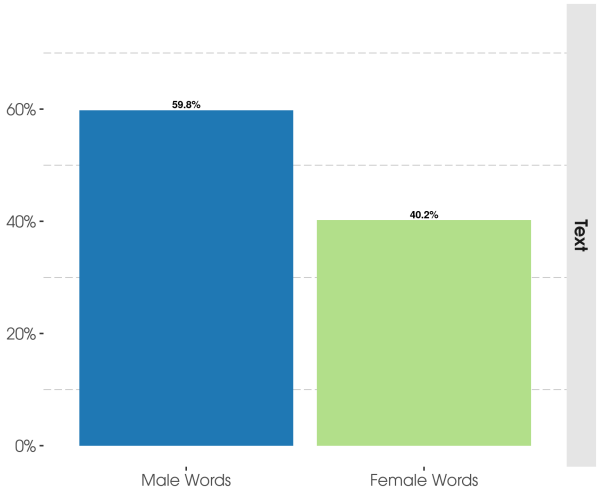
Note: In this figure, we plot female faces by race as a proportion of all faces with a given race classification on the y-axis and famous female characters by race as a proportion of all famous characters with a given race classification on the x-axis.

Figure A18. Hand-Coded Measures of Representation



Note: In this figure, we show hand-coded measures of gender and race representations from a sample of 30 short stories and poems written for children. In Panel A, we show the percent of characters (either pictured as in the top row or mentioned in the text as in the bottom row) that were coded as male, female, or unspecified. In Panel B, we show the percentage of pictured human characters in each skin color classification based on the Fitzpatrick scale (Pathak et al., 1976).

Figure A19. Measures of Representation Collected Using AI and Natural Language Processing Tools



Note: In this figure, we show measures of gender collected using natural language processing tools from a sample of 30 short stories and poems written for children. We show female and male words as a percentage of all gendered words (e.g., pronouns, gendered tokens, gender predictions of famous characters, and gendered character names).

C.3 Data Appendix

C.3.A Seattle Public Library Checkouts Data

To study the impact of being honored by the children's book awards we examine, we analyze data from the Seattle Public Library system on all public checkouts from the library between April 2005 and September 2017.[70] Awards are given in late January each year, to books published in that year or the year before. We analyze checkout data for the award-winning books in our data, alongside a random sample of ten percent of all books in the children's and junior book collections published in the year prior to the award, covering the award years 2005 to 2017.[71]

We collapse these to a dataset of collection-by-day checkout likelihoods, divided by the number of books in the collection to generate a measure of the number of checkouts per book, per day, in each of the three collections. We censor checkout data for each book to the calendar year before the award was given and the two following calendar years.

To generate Figure 2, 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 2010 would be eligible for an award in 2011. Checkouts from before February 1, 2011 would be given negative values – for example, checkouts on January 30th, 2011, would be –2 days from February 1, 2011. Checkouts after that date have positive values. Figure 2 shows the results of applying a local polynomial smoother 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 non-winner collections) over the window of days to award spanning [–365 days, 730 days].

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 receipt of an award or honor, relative to the rest of the sample. 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 number of checkouts, per book, in collection c on day d. We

[70] These data are publicly available at https://www.kaggle.com/seattle-public-library/seattle-library-checkout-records; we accessed it on April 15, 2021.

[71] We sample ten percent of all these books for ease of computation; this comprises over 25 million checkout records, as opposed to the more than 260 million checkout records in the full dataset.

regress this on the following variables: whether the day is after February 1st (*Post*) (a noisy estimate of the date when the awards are announced each year); a set of fixed effects for each collection; and an interaction of the *Post* variable with the *Mainstream* and *Diversity* collection variables. Our main coefficients of interest are β_2 and β_3.

Table A5. Estimates of the Increase in Checkouts After Receipt of Mainstream and Diversity Awards

Parameter	**Estimate**
Post x Mainstream collection (β_2)	0.1032**
	(0.0038)
Post x Diversity collection (β_3)	0.0039
	(0.0038)
Post (β_1)	0.0211**
	(0.0027)
Mainstream collection fixed effect	0.0480**
	(0.0022)
Diversity collection fixed effect	0.0547**
	(0.0022)
Non-winners fixed effect	0.0734**
	(0.0022)
R^2	0.5003
Observations	3,375

Table notes: These parameters were generated using the equation given in this subsection of the Data Appendix estimated using data from the Seattle Public Library on daily checkouts. The Diversity collection is the "baseline" category, so the Mainstream and non-winner fixed effects are in reference to the checkout rate for it. Statistical significance is denoted by * for $p < 0.05$ and ** for $p < 0.01$.

We present our results in Table A5. This shows that after winning an award, Mainstream books are approximately twice as likely as (82.3 percent more than) non-winners 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-winners. For the Mainstream books, this is the sum of the constant, 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 0.1723. The post-award checkout rate for non-winners is the sum of the *Non-winners* fixed effect and the coefficient on *Post*, which sums to approximately 0.0945. Prior to receiving an award, on the other hand, the Mainstream collection books were approximately 35 percent *less* likely to be checked out than non-winners.

An alternate interpretation is that after winning the award, the Mainstream collection books are approximately 2.6 times more likely to be checked out than they were before. This is derived by dividing the sum of coefficients on *Post* (0.0211), the interaction of *Mainstream* and *Post* (0.1032), and the *Mainstream* fixed effect (0.0480) by the *Mainstream* fixed effect. We note that these should be interpreted as suggestive estimates; we define "pre-" and "post-" award using February 1st, 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 no significant change in checkout behavior after February 1st. This can be seen in our estimate of the interaction term between *Diversity* and *Post*, which is small in magnitude and not statistically distinguishable from zero. Seen through the lens of the calculations above, after receiving an award, Diversity collection books are more than 15 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 0.0797. 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 0.0945. Prior to receipt of the award, they were approximately 25 percent less likely to be checked out, but the statistical insignificance of the interaction between the *Post* and *Diversity* (Post x Diversity) variables means that we cannot reject the null hypothesis that the pre-award and post-award differential checkout rates between Diversity collection books and non-winners is zero.

C.3.B Text Cleaning

The current data cleaning process standardizes the following names, which may have variants in how they are written: abraham lincoln, martin luther king junior, rosa parks, eleanor roosevelt, harriet tubman, george washington.

Our current data cleaning process also removes alpha consecutive lines with no more than beta words. Currently, we use a value of four for alpha and three for beta. This is meant to serve as a way to remove copyright pages or indices.

This process generates a list of words, also known as tokens, which we aggregate to generate "token counts," or measures of frequency of the mention of specific words.[72]

C.3.C All Gendered Mentions

The total number of female words in book i is calculated as follows:

$$\begin{aligned}(\text{female words})_i = &(\text{total number of female-specific tokens})_i \\ &+ (\text{total number of mentions of famous female characters})_i \\ &+ (\text{total number of characters with female first names})_i\end{aligned}$$

C.3.D Specific Token Counts

The list of specific tokens (words) that we use in our text analysis are listed below.

Gendered Tokens. The gendered tokens we enumerate are as follows. Subset lists are used for the specific gendered token counts, gendered pronouns, singular/plural gendered token counts, younger/older gendered token counts and uppercase/lowercase pronouns.

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

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,

[72]This differs slightly from the notion of "lemmas," which are measures of the count of word stems. To understand the difference, take the words "father," "fatherly," and "fathered." If each word appeared once in a book, it would generate a token count of one for each word, but a lemma count of three for the lemma "father."

papa, papas, prince, princes, sir, sirs, son, sons, squire, squires, stepfather, stepfathers, tio, tsar, uncle, uncles, waiter, wizard, wizards

Racial Proxy Tokens. The tokens we use as proxies for race are as follows.

Colors. The color word tokens used as proxies for race and falsification words are the following: black, blue, brown, gold, golden, green, orange, pink, purple, red, silver, violet, white, yellow. For parsimony, in the paper we only show the words black, blacks, white, whites, blue, and blues.

Nationalities. Afghan, African, Albanian, Algerian, American, Andorran, Angolan, Antiguans, Apache, Argentinean, Armenian, Asian, Australian, Austrian, Azerbaijani, Bahamian, Bahraini, Bangladeshi, Barbadian, Barbudans, Batswana, Belarusian, Belgian, Belizean, Beninese, Bhutanese, Bolivian, Bosnian, Brazilian, British, Bruneian, Bulgarian, Burkinabe, Burmese, Burundian, Cambodian, Cameroonian, Canadian, Cape Verdean, Chadian, Cherokee, Chicana, Chicano, Chicanx, Chilean, Chinese, Choctaw, Colombian, Comoran, Congolese, Croatian, Cuban, Cypriot, Czech, Danish, Djibouti, Dominican, Dutch, Dutchman, Dutchwoman, Ecuadorean, Egyptian, Emirian, English, Eritrean, Estonian, Ethiopian, Fijian, Filipino, Finnish, French, Gabonese, Gambian, Georgian, German, Ghanaian, Greek, Grenadian, Guatemalan, Guinea-Bissauan, Guinean, Guinean, Guyanese, Haitian, Herzegovinian, Hispanic, Honduran, Hungarian, Icelander, I-Kiribati, Indian, Indonesian, Iranian, Iraqi, Irish, Irish, Iroquois, Israeli, Italian, Ivorian, Jamaican, Japanese, Jordanian, Kazakhstani, Kenyan, Kittian, Korean, Kuwaiti, Kyrgyz, Laotian, Latina, Latino, Latinx, Latvian, Lebanese, Leonean, Liberian, Libyan, Liechtensteiner, Lithuanian, Lucian, Luxembourger, Macedonian, Malagasy, Malawian, Malaysian, Maldivan, Malian, Maltese, Marinese, Marshallese, Mauritanian, Mauritian, Mexican, Micronesian, Moldovan, Monacan, Mongolian, Mongols, Moroccan, Mosotho, Motswana, Mozambican, Namibian, Nauruan, Navajo, Nepalese, Netherlander, Nevisian, Nicaraguan, Nigerian, Nigerien, Ni-Vanuatu, Norwegian, Ojibwe, Omani, Pakistani, Palauan, Panamanian, Paraguayan, Persian, Peruvian, Polish, Portuguese, Qatari, Rican, Romanian, Russian, Rwandan, Salvadoran, Samoan, Saudi, Scottish, Senegalese, Serbian, Seychellois, Singaporean, Sioux, Slovakian, Slovenian, Somali, Spanish, Sri-Lankan, Sudanese, Surinamer, Swazi, Swedish, Swiss, Syrian, Taiwanese, Tajik, Tanzanian, Thai, Timorese, Tobagonian, Togolese, Tomean, Tongan, Trinidadian, Tunisian, Turkish, Tuvaluan, Ugandan, Ukrainian, Uruguayan, Uzbekistani, Venezuelan, Vietnamese, Welsh, Yemenite, Zambian, Zealander, Zimbabwean