We are the Data: Challenges and Opportunities for Creating Demographically Diverse Anthropographics

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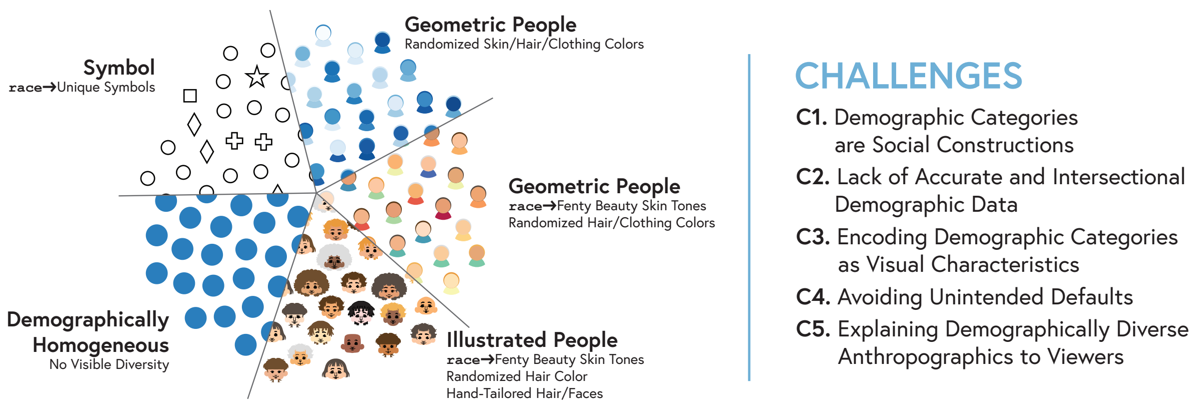

Figure 1: A unit visualization showing five approaches for visualizing data about individuals. We examine trade-offs between *demographically homogeneous anthropographics* (like the blue circles in the lower left) and *demographically diverse anthropographics* that visually encode real or simulated demographic data, and identify challenges for creating these representations.

ABSTRACT

Anthropographics are human-shaped visualizations that aim to emphasize the human importance of datasets and the people behind them. However, current anthropographics tend to employ homogeneous human shapes to encode data about diverse demographic groups. Such anthropographics can obscure important differences between groups and contemporary designs exemplify the lack of inclusive approaches for representing human diversity in visualizations. In response, we explore the creation of *demographically diverse anthropographics* that communicate the visible diversity of demographically distinct populations. Building on previous anthropographics research, we explore strategies for visualizing datasets about people in ways that explicitly encode diversity—illustrating these approaches with examples in a variety of visual styles. We also critically reflect on strategies for creating diverse anthropographics, identifying social and technical challenges that can result in harmful representations. Finally, we highlight a set of forward-looking research opportunities for advancing the design and understanding of diverse anthropographics.

CCS CONCEPTS

• **Human-centered computing → Visualization design and evaluation methods**.

KEYWORDS

anthropographics, demographic data, diversity, marginalized populations

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1 INTRODUCTION

Human-shaped visualizations, sometimes called *anthropographics* [7] have been widely used by designers and researchers to show data about people—often with the intent of using these human shapes to help viewers better connect with the data. This approach follows conventional thinking in visual arts where, as McCloud argues [34], homogeneous human shapes are abstractions that can be understood as representing people generally. Thus, most current anthropographics are demographically homogeneous and tend to employ generic human-shaped templates that do not encode identifiable physical characteristics and are visually repeated to represent demographically distinct groups of people.

At the same time, anthropographics are often used to represent data with demographic components (such as data about race, gender, or disability). Since the collection and use of demographic data frequently involves grouping individuals based on observable human characteristics (such as skin color, hair color, and facial features)

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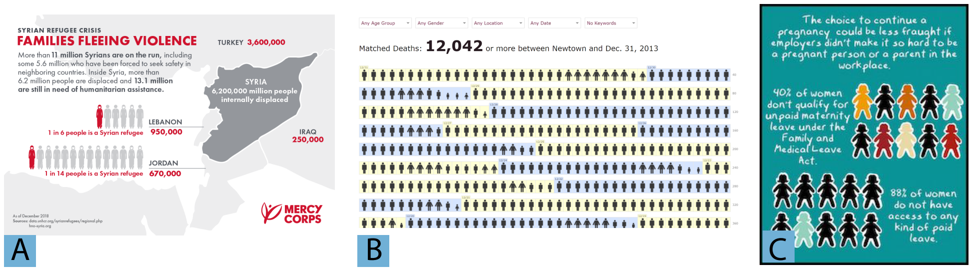

Figure 2: Examples of current anthropographics from data journalism. From left to right: (A) More diverse human-shaped icons representing Syrian refugees from "Quick Facts: What You Need to Know about the Syria Crisis" by *Mercy Corps* [12]. (B) Simple human-shaped icons of victims of mass shootings from "How Many People Have Been Killed by Guns Since Newton" by *Slate* [28]. (C) Demographically homogeneous illustrations of women in the US from "The Economic Case for Abortion Rights" by *Aubrey Hirsch for Vox Media* [23].

demographic data is closely linked to experiences of marginalization. Indeed, demographic classifications have long been (and are still) used to discriminate against and marginalize people through systems of oppression such as ageism, racism, and sexism [3]. Our work focuses on anthropographics of populations that have been marginalized based on visible race demographic characteristics as defined in the US and Canada. Race as demographic data has historically been constructed from physical characteristics such as skin color [26], often ignoring the wide variations in characteristics among individuals who are grouped in the same racial category. The process of assigning individuals to racial categories based on appearance is an unconscious but frequent occurrence and previous work in psychology has established that individuals primarily use skin color for at-a-glance racial identification [22]. To avoid perpetuating stereotypes of marginalized populations, designers frequently do not encode race as skin color but have tended to use default designs, such as yellow emoji, to avoid the association with specific demographic groups. Yet, as Robertson et al. [45] point out, marginalized populations do not interpret the default design of the yellow emoji as truly default but rather associate it with a White identity—challenging the assumption that generic human shapes can truly represent demographically diverse individuals or groups.

The use of demographically homogeneous anthropographics becomes more problematic when used to represent distinct marginalized populations without showing their physical diversity, as it erases visible demographic differences between them that may also be linked to their experiences of marginalization. The choice to omit demographic characteristics in anthropographics can be intentional or unintentional and often depends on the purpose of the visualization. One such example is the *New York Times* visualization of COVID-19 deaths [5] where a set of similar human shapes is used to represent individuals who died of the disease. This aesthetic was likely intended to convey a sense of togetherness and loss for readers experiencing the pandemic, but at the same time hides important demographic differences such as race, gender, and social class—despite the fact that many of these demographic differences also likely influenced individuals' COVID exposure and cause of death [10, 27]. The use of generic human shapes to represent populations with different demographic and physical characteristics can also unintentionally obscure distinctly different cultures and lived experiences, treating them as interchangeable. For example, in their experimental studies of anthropographics for eliciting empathy, Boy et al. [7] employed the same human-shaped icons to represent groups of Syrian children experiencing different crises. Similarly, Morais et al. [36] used the same anthropographic designs to visualize data about migrants from two different geographical locations (the Middle East and Southeast Asia) who were experiencing different crises—without showing differences in physical diversity between them.

To address these possible limitations of demographically homogeneous anthropographics, we explore the creation of **demographically diverse anthropographics** that can communicate the demographic differences between people and emphasize that they are not interchangeable. Demographically diverse anthropographics align with previous work on inclusive visual representations of race and gender by Passmore and Mandryk [41], which underlines the lack of inclusiveness in current approaches for visually representing physical diversity. A lack of inclusive options for representation can also signal to marginalized populations that diversity is an afterthought in design processes [41]. By using visual representations whose appearance reflects the diversity of real human populations, demographically diverse anthropographics may increase the credibility of visualizations about people. Demographically diverse anthropographics can also be useful for data storytelling in situations where a people-centric model may be preferable to a statistical one—such as combatting bias or raising awareness about sensitive issues like migration (as previous work by Liem et al. has suggested [31]). Furthermore, studies examining demographically diverse anthropographics can help designers understand how marginalized populations perceive anthropographics and how (or if) they wish to be represented.

Previous work in anthropographic research has yet to explore the creation of demographically diverse anthropographics that encode physical characteristics and convey the demographic differences between people. While Boy et al. and Morais et al. [7, 35] proposed two design spaces for the creation of anthropographics, existing work does not analyze the data and the design decisions behind their creation. To explore and elucidate the challenges and potential of demographically diverse anthropographics, we build on these two design spaces [7, 35] by prototyping, examining, and critiquing new examples of demographically diverse anthropographics.

This work is the first to explore the creation of demographically diverse anthropographics from demographic data with an awareness of racial equity, while taking a critical stance to also identify challenges and opportunities in this area. We offer three contributions. First, we describe a series of prototypes and design explorations that illustrate potential approaches for creating anthropographics that communicate human diversity. Second, building on these examples and our experiences designing them, we identify a set of open technical and social challenges inherent in the creation of demographically diverse anthropographics. Finally, we highlight opportunities for further research that can improve our understanding of the impact of anthropographics and how to create them in more inclusive ways.

2 RELATED WORK

We situate our work within research on anthropographic visualization, critical visualization, and critical data science.

2.1 Anthropographic Visualization

Anthropographics are an emerging subfield within visualization research that has primarily focused on measuring the effectiveness of human-shaped visualizations at provoking prosocial feelings. Previous work has included the creation of two design spaces for anthropographics and a series of experiments that encode some demographic data [7, 35, 36]. Recent work has also explored the use of distinct anthropographic designs in data storytelling [25, 31], suggesting other potential uses of anthropographics. Early work by Boy et al. proposed a design space for creating anthropographics from human-shaped icons, including specifications for the type (unit or aggregate) of visualizations, the realism and expressiveness of the human shapes used (Figure 3-top), and several other factors that affect their design [7]. Boy et al. also conducted a series of donation allocation experiments where they encoded data about children experiencing the Syrian crisis using simple, homogeneous 2D human-shaped icons [7]. Subsequent work by Morais and colleagues [35] included an alternative design space that proposes seven dimensions focusing on what information the anthropographics convey (granularity, specificity, coverage, authenticity) and how (realism, physicality, situatedness) [35]. Demographically diverse anthropographics share several dimensions outlined by Morais et al. [35], namely authenticity (the number of genuine attributes in a dataset), coverage (the number of people from the original dataset that are included in the resulting visualization), specificity (how distinct the attributes are in a dataset), and realism (how closely the resulting anthropographics resemble the people in the dataset).

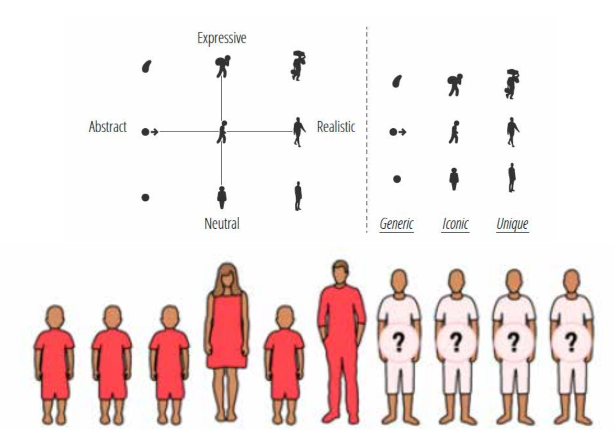

Figure 3: (top) Excerpt from the design space proposed by Boy et al. [7] showing realism and expressiveness of anthropographics. (bottom) Demographically homogeneous anthropographics showing age and gender data for migrants from the Middle East and Southeast Asia used in Morais et al.'s donation study [36].

In a separate study, Morais et al. [36] conducted a number of large-scale donation experiments using demographic data about migrants from the Middle East and Southeast Asia. Specifically, Morais et al. encoded age and gender using a set of three human shapes (Figure 3-bottom) representing a child, an adult woman, and an adult man [36]. They used this set of demographically homogeneous anthropographics to represent two demographically distinct migrant groups from two different geographical regions and who died of different causes [36]. While Morais et al.'s [36] designs encoded more demographic data and portrayed more physical characteristics compared to Boy et al.'s use of simple human icons [7], prior work has yet to provide guidance for how to encode the demographic data and communicate physical differences between the populations being represented.

Considering other uses of anthropographics, Liem et al. [31] used six distinct anthropographic designs for storytelling—visualizing the migration paths of six fictional characters to gauge attitudes towards migration in the UK. Each of these anthropographics used human shapes with varying sizes to show age and also included details such as hair and clothing [31]. Similarly, in their experimental immersive anthropographic visualizations, "A Walk among the Data", Ivanov et al. [25] encoded the gender and age of victims of mass shootings in the US but specifically chose not to represent the physical characteristics of the victims due to a lack of available data about their appearances. Our work attempts to bridge this gap by examining approaches for creating anthropographics that explicitly encode demographic data and incorporate physical characteristics.

2.2 Critical Visualization

The creation of diverse anthropographics is directly related to approaches in critical visualization that advocate for equitable research practices when working with marginalized populations. Within visualization research, Dörk and colleagues [18] propose that designers consider critical approaches that prioritize contingency, disclosure, empowerment, and plurality when evaluating visualizations. Additionally, they emphasize that visualizations are situated, are influenced by the intentions of the designer, and also frequently surface issues within datasets that might not be immediately visible [18]. Recent thinking in critical visualization has also suggested the existence of unwanted effects that might influence how viewers perceive or interact with visualizations. For example, Correll [13] mentions how viewers can often experience feelings of alienation from the people being represented by visualizations. Meanwhile, in their study of data receptivity among participants in rural Pennsylvania, Peck et al. [42] concluded that for some viewers, familiarity with data is an important but extremely personal factor that influences how they relate to a visualization. From a practitioner perspective, Schwabish and Feng [46] in their *Do No Harm* guide advocate for critical approaches that include equitable design practices and an awareness of racial equity in visualization. Several of these guidelines—such as considering privacy when data for marginalized populations is below a certain threshold and examining choices made during the design process [46]—are also central to the creation of demographically diverse anthropographics.

Our design explorations and examples of demographically diverse anthropographics are also motivated by an awareness of racial equity. In their work adapting critical race theory for use in HCI research, Ogbonnaya-Ogburu et al. [39] advocate for race-conscious research by emphasizing that racism is pervasive in daily life and is consequently embedded in HCI research. One example they propose in their call to action [39] is research that explores how visualizing race-based data can show context to mitigate stereotypes about marginalized populations. Our design explorations similarly exemplify potential race-conscious approaches for data visualizations that foreground racial diversity.

2.3 Critical Data Science

Within critical data science, D'Ignazio and Klein [17] emphasize the existence of power imbalances when working with data involving marginalized populations. They propose an intersectional feminist lens to question existing power structures such as hierarchies between researchers and participants, and for disrupting inequitable practices—particularly the use of classification systems such as gender binaries that perpetuate discrimination [17]. Similarly, on issues related to datasets, Gebru et al. [21] have proposed *Datasheets for Datasets* for researchers working with machine learning data, which include guidelines to address concerns around potential bias. These include consulting with domain experts when datasets (such as data about marginalized populations) require additional scrutiny [21]. We highlight several challenges and potential pitfalls of anthropographics later in Section 4 that intersect with these considerations.

3 CREATING DIVERSE ANTHROPOGRAPHICS

Building on previous work on the design of anthropographics, we conducted a series of prototyping and design exercises to explore various strategies for creating anthropographics that represent demographic data by varying physical diversity characteristics. We define *demographically diverse anthropographics* as human-shaped visualizations that emphasize the human diversity of the populations being represented. To explore the implications of creating these kinds of graphics, we first considered several approaches for visually representing human diversity. These included varying visual style and physical characteristics such as skin tone, as

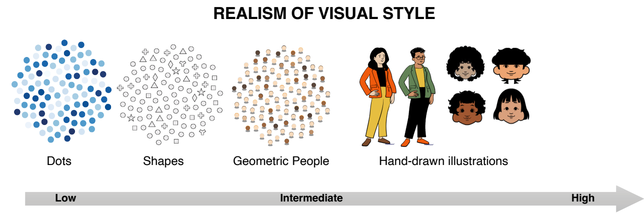

Figure 4: Visual styles showing dots, shapes, geometric people, and hand-drawn illustrations (including our own and Open Peeps [49]).

well as considering different kinds of data sources that designers might use to produce demographically diverse anthropographics. Our prototypes and design explorations are meant to be generative, surfacing potentially problematic strategies and challenges for representing demographic data, which we describe in Section 4. As a result, the approaches we explore in this work do not necessarily reflect how individuals belonging to diverse and underrepresented demographic groups may choose to visually represent themselves.

Perhaps the most straightforward approach for representing human diversity is to encode it by varying **physical diversity characteristics** in the anthropographics—including skin tone, hair color, facial features, and other factors that are typically used to classify individuals into demographic groups. However, the limitations of demographic data and decisions associated with encoding these demographics as physical characteristics pose a variety of challenges for designers. These decisions are also impacted by the **visual style** of anthropographics, with more complex human shapes and illustrations creating more opportunities for encoding diversity than simple geometric marks—but also greater complexity and opportunities for problematic encodings. Visual styles can also vary in expressiveness and realism [7], as well as authenticity, specificity, and coverage [35], depending on factors such as the design resources available and the intended use of the visualization.

Creating anthropographics that authentically represent human diversity ideally calls for both **demographic data** about the visualized population and accurate **mappings** from those demographics to physical diversity characteristics. However, given that most datasets about people lack information on demographics and physical diversity characteristics, other data sources may often be necessary. These can include population-level demographic data collected by national censuses, as well as global, national, or regional data that quantifies physical diversity characteristics like height, weight, or skin tone. If population-level data is not available or does not exist, simulating or randomly sampling to approximate population diversity may be possible, but also increases the risk of creating inaccurate or problematic representations of diversity.

3.1 Methodology

To examine the potential, pitfalls, and complexities associated with these design facets, we spent roughly four months prototyping and creating mockups of new demographically diverse anthropographics. Our initial rounds centered on a set of ReactJS prototypes that used hand-drawn illustrations from the Open Peeps image collection [49] to create highly-expressive human figures. Next, we created an interactive set of Observable notebooks that used D3.js to generate a variety of simpler and more scalable anthropographic designs, which allowed us to experiment with a range of demographic data sources and physical diversity mappings. Throughout, we complemented these prototypes with designs produced using hand illustration and vector graphics tools like Adobe Illustrator. Interactive versions of our Observable prototypes are available at https://observablehq.com/@data-experience-lab/we-are-the-data-geometric-people-prototype.

Two of the authors (Dhawka and Willett) met on a weekly basis over the course of three months to discuss each iteration of our designs. In parallel, we also iteratively discussed, described, and characterized the design choices behind our prototypes, incorporating the other author (He) periodically to provide a critical outside perspective on our approaches and their framing. During this process, we reflected on the challenges we encountered and brainstormed future research opportunities, both of which we synthesize later in Sections 4 and 5.

3.2 Design Explorations

Our prototypes and other designs, a selection of which we share in the following sections, illustrate how the underlying data, visual style, and other design choices can change the visual impact of anthropographics. In order to support comparison across design choices, the majority of our designs use the same underlying data but vary visual style and encodings. Each of the anthropographics in the following sections is a representation of the same dataset, showing 100 individuals generated via random sampling from US census summary data tables [8]. We use demographic data simulated from the US census for the following eight race categories: *American Indian* (abbreviated as "Am.Ind" in our figures), *Asian*, *Black*, *Hispanic or Latino* ("Hisp."), *Native Hawaiian* ("Nat.HI"), *Other*, *Two or More* ("Multiple"), and *White* [8]. These category labels for race are taken from the US census, including the "Other" category which corresponds to "racial categories not listed in the US census". Due to some demographic groups (such as Native Hawaiian) making up a smaller percentage of the US population, our demographic data does not include these in smaller sample sizes. We chose to focus primarily on race information because it is one of the most frequently collected forms of demographic data in the US and Canada and is socially seen (often erroneously) as being connected to visible markers of human diversity like skin tone and hair color. This makes it one of the most likely candidate data sources for creating demographically diverse anthropographics, but also one that can be deeply problematic, and our choice to examine it reflects an effort to confront those challenges directly in hopes of elucidating them more clearly.

To support visual comparison, all of the graphics in the following sections show a unit visualization, which includes the same set of 100 individuals organized in an identical phyllotaxis layout. While we use a single generic layout here for simplicity, the graphical encodings we demonstrate could also be used in most other unit visualization designs. To highlight the sampling, encoding, and data binding choices, each example also includes an aggregate histogram (illustrated in Figure 5) that shows the distribution of individuals across race categories and highlights the relationship between those categories and any primary color encodings applied to the chart.

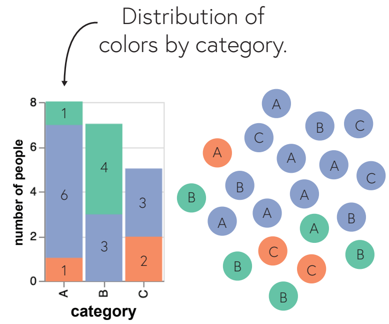

Figure 5: Figures in the following section show the number of people organized by category and color encoding.

Given the exploratory nature of this work, its use of high-level census data, and the fact that it surfaces potentially harmful representations, we did not directly test how individuals perceive or react to these kinds of diverse anthropographics. However (as we detail in Section 5), we believe that incorporating the individuals being represented into the process of designing demographically diverse visualizations and evaluating their impact remain important next steps for this research area.

3.2.1 Demographically Homogeneous Anthropographics. As a point of comparison and baseline, Figure 6 showcases three examples of demographically homogeneous anthropographics to contrast with our demographically diverse anthropographics. Throughout our design explorations, we considered non-anthropomorphic shapes like circles (which can be be modified to encode diversity characteristics like skin tones) and simple geometric people (which use an iconic human shape and add stylable hair and clothing). We acknowledge that creating diverse anthropographics can be time-consuming and may be limited by a designer's access to resources. To address these concerns, we experimented with simple non-anthropomorphic shapes to find accessible ways of encoding diversity within standard visualizations. Figure 6 includes a non-human (blue) skin tone encoded as circles, geometric people with a single human skin tone (Fenty Beauty foundation shade 300) and geometric people with a single non-human (grey) skin tone. These demographically homogeneous encodings are similar (albeit slightly more abstracted) to most of the current examples of demographically homogeneous anthropographics in data journalism and visualization. For instance, the blue circles use a single non-human color, a common approach in contemporary unit visualizations of demographic data. The grey geometric people, meanwhile were inspired by The New York Times visualization of lives lost during the COVID-19 pandemic [5] and the geometric people with the Fenty Beauty foundation shade 300 were inspired by the anthropographics of migrants from the Middle East and South East Asia from the study by Morais et al. [36] that use a single skin tone for both migrant groups.

3.2.2 Suggesting Human Diversity using Color. Perhaps the simplest approach to suggesting diversity in anthropographics is to

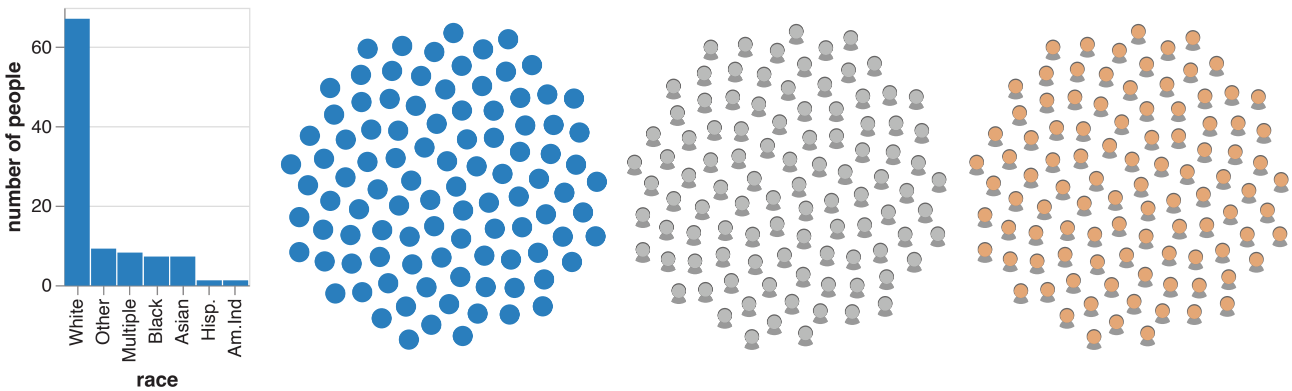

Figure 6: Demographically homogeneous representations of 100 individuals using circles (second from the left), neutrally-colored geometric people (center), and geometric people colored with a median skin tone based on Fenty Beauty foundation shade 300 (right). Underlying demographic categories (visible in the leftmost histogram) are not encoded.

introduce random color variations to the marks—creating visual differentiation and variety without relying on any underlying data. Figure 7 highlights examples from our prototyping that use both continuous and categorical versions of this approach.

Here, the continuous version randomly samples skin, hair, and clothing colors for each individual from a continuous blue color scale, while the categorical version does the same from an 8-color palette. Because these encodings specifically do not take into account the underlying distribution of demographic data, they give a sense of variation within the population but do not allow viewers to extract any real demographic information. (However, we suspect that many viewers may still implicitly interpret variations in luminosity as darker or lighter skin tones).

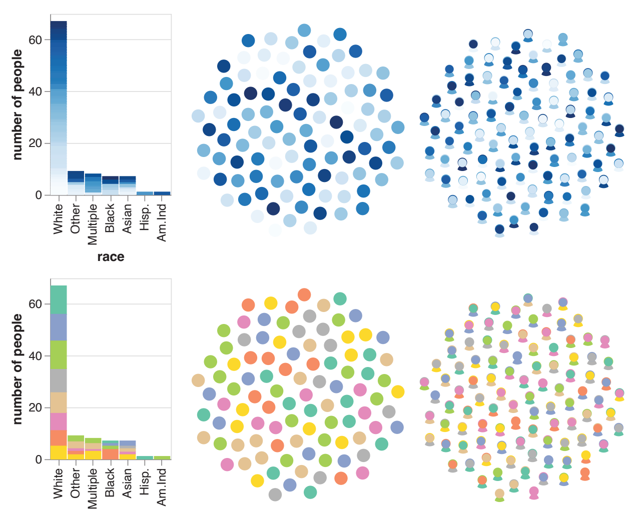

Figure 7: Circles (left) and geometric people (right) with randomly-assigned continuous (top) and categorical (bottom) colors. These color encodings suggest diversity in abstract but are not data-driven.

3.2.3 *Using More Representative Human Skin Tones.*

Introducing diversity by using a range of human-like skin tones has the potential to more directly suggest human racial, ethnic, or cultural diversity. This approach is common in a variety of non-visualization settings, including communication and advertising, where character illustrations and other graphics with human skin tones are often used to signal inclusion and diversity. Similarly, the Unicode consortium's introduction of a limited set of skin tone modifiers for emoji has resulted in their increased use as a way of suggesting multicultural group composition [45].

During our prototyping and experimentation, we examined several approaches that use more representative skin tones to show physical diversity between and within racial categories. Our early explorations built directly on the Unicode emoji skin tone modifiers, a set of colors that map roughly to the numerical categories from the Fitzpatrick skin type classification [37]. This scale (which for simplicity we refer to as "Fitzpatrick tones") contains five skin tones ordered from light to dark. We experimented with this scale due to a lack of standardized color palettes for skin tones and because the Fitzpatrick skin type classification is widely used in other areas such as dermatology, making it easily accessible to designers. However, this scheme is widely recognized as having too few categories and captures an extremely unrealistic subset of human skin tones.

In response, we also explored designs using a broader and more representative set of colors based on foundation tones from the Fenty Beauty makeup brand [6]. This brand was the earliest beauty brand to offer an extensive and inclusive range of makeup shades for a wide range of complexions, with particular emphasis on capturing the dark tones absent from traditional makeup lines [1]. We chose skin tone color palettes from this brand to create diverse anthropographics with an awareness of racial equity. The collection contains fifty distinct foundation colors organized into four bands (*light* tones with designations in the 100s , *medium* tones in the 200s , *tan* tones in the 300s , and *deep* tones in the 400s range) with individual shades varying from warm to cool.

Using these tones, we prototyped numerous anthropographic designs. Acknowledging the complexity of creating diverse anthropographics, we considered a range of types of anthropographics that a designer may create, depending on the resources available to them and the intended use of the visualization. These include versions that apply the tones to simple shapes (like Figure 8-left) as well as anthropographic designs. For example, the visualizations in Figure 8-right use these palettes to randomly assign skin tones to simple geometric people, and combine these with randomly assigned hair colors drawn from Google's Noto Color Emoji 🧑🏻 🧑🏿 🧑🏼 🧑🏽 🧑🏾 🧑‍🦰, which we also chose due to a lack of existing datasets of demographic data and hair color. Compared to the broader range of colors demonstrated in the previous examples, these skin tone encodings are more immediately read as showing a diverse human population. However, these two produce substantially different-looking visualizations, with the Fitzpatrick colors (Figure 8-top) appearing darker and cooler with only a few distinct variations, while the Fenty Beauty colors (Figure 8-bottom) are both warmer and lighter overall and exhibit more continuous variation. These visual differences highlight the impact that specific color choices might have, and the extent to which each may or may not be able to capture the variation in a given real-world population. In these examples, our random assignment of colors irrespective of the underlying demographic data also means the appearance of the visualization is unlikely to reflect that of the population it represents—which may lead viewers to question the encoding or even the credibility of the visualization.

3.2.4 Mapping Race to Skin Tones. Assigning skin tones based on demographic categories like race or ethnicity, while superficially straightforward, entails a set of consequential design decisions which present opportunities for problematic (and potentially even racist) visualizations. To illustrate these challenges, we prototyped and critiqued a variety of different strategies for mapping race to skin tone, including the examples in Figure 9, which show three different mappings of our sample data to the Fenty Beauty tones.

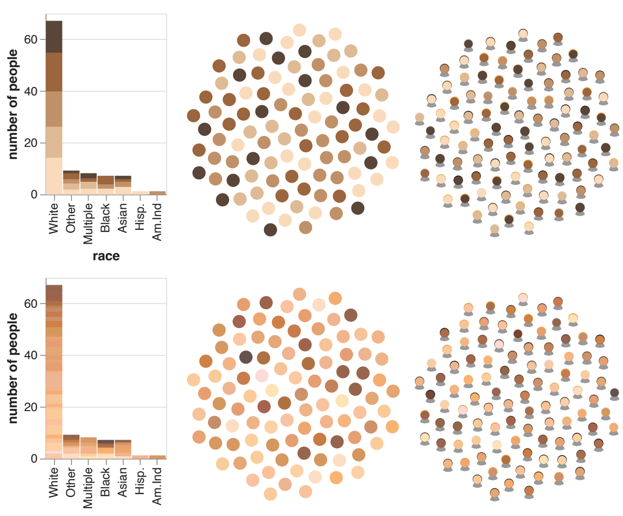

Figure 8: Circles (left) and geometric people (right) with randomly-assigned colors from the Fitzpatrick (top) and Fenty Beauty (bottom) color sets more strongly suggest human racial, ethnic, or cultural diversity. However, these colors do not correspond to the underlying data.

Randomly assigning skin colors to individuals (as in Figure 8), while possible at a population level, quickly becomes problematic in visualizations (like Figure 9-left) which either implicitly or explicitly surface demographic data which might conflict with viewers' assumptions about the tones. In response, designers can choose to map categories such as race or ethnicity to specific skin tones. However, this requires designers to make specific assumptions about which skin tone(s) to map to each category. Different mappings can result in substantive differences in the visual appearance of the encodings and—since demographic categories are social constructions—these decisions introduce considerable opportunity for designer bias.

For example, in Figure 9-center we illustrate the effect of assigning wide (although potentially still exclusionary) bands of skin tones to both the White and Black race categories—mapping individuals with the White category label to Fenty Beauty tones in the 100s–200s and individuals with the Black category label to tones in the 300s–400s then randomly sampling from the complete set of tones for the individuals in the other six categories. Figure 9-right, meanwhile, illustrates a more restrictive strategy—assigning only skin tone bands in the 100s to White and only tones in the 400s to Black. To varying degrees, these two strategies align with ways in which individuals have historically been classified into arbitrary racial categories [26]. As a result, the skin tone composition of the resulting visualizations is more likely to resemble that of a real human population with these census labels than the purely random variant, and is also less likely to produce individual race-to-tone mappings that seem implausible to viewers. However, in doing so these designs make questionable and potentially damaging assumptions about the identities of the individuals that the visualization represents.

3.2.5 Increasing Realism and Visual Expressiveness. While the previous examples we have used showcased simple non-human shapes and geometric people with low visual realism, increasing the realism level of anthropographics creates a variety of new opportunities for encoding demographic characteristics. To explore the trade-offs associated with increasing visual realism and expressiveness, we created a range of illustrated anthropographics that represent individuals using hand-sketched figures and composable characters from the Open Peeps image collection [49]. We also developed our own set of composable character illustrations which feature more easily stylable skin as well as hairstyles.

Using both our illustrated and geometric figures, we conducted design explorations based on several existing anthropographic visualizations from data journalism that feature underrepresented populations. Here, we re-created pieces of the existing graphics using multiple different visual styles that allowed us to encode additional demographic detail and introduce more expressive human shapes. Figure 10 shows a sample of our re-creation of a data story by *The New York Times* titled "Extensive Data Shows Punishing Reach of Racism for Black Boys" [4]. This story describes the

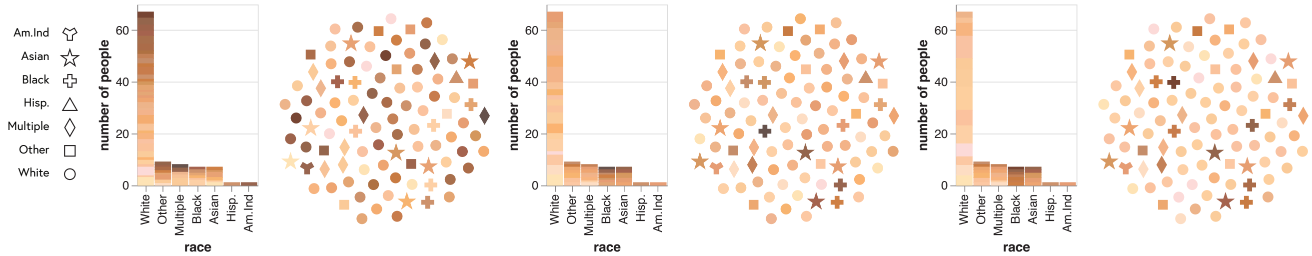

Figure 9: Three visualizations encode underlying race categories from the US census using symbols and colored with Fenty Beauty skin tones. (left) Tones are assigned randomly to individuals. (center) Fenty tones in the 100s and 200s colors assigned to the White category and 300s and 400s assigned to the Black category. (right) Tones in the 100s assigned to White and 400s to Black. Each mapping produces a visualization with different (and potentially problematic) implications.

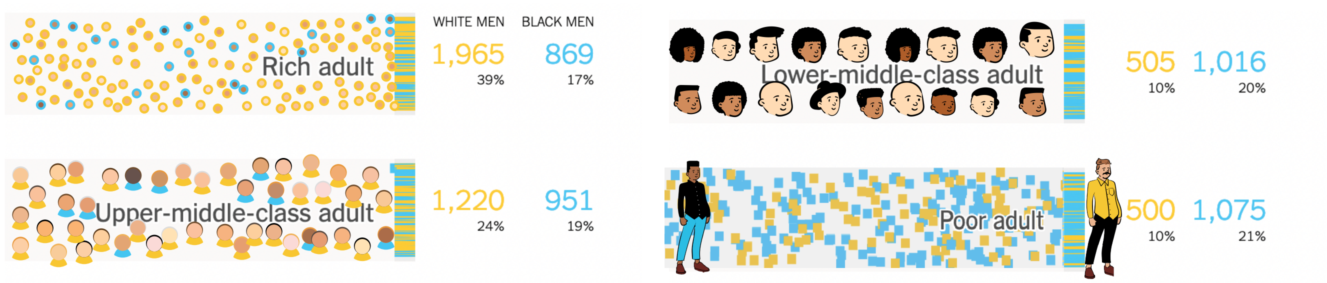

Figure 10: Varying strategies to introduce diversity in an existing visualization from"Extensive Data Shows Punishing Reach of Racism for Black Boys" by *The New York Times* [4]. Circles (top left) showing "Rich adult", geometric people (bottom left) encoding skin tones showing "Upper-middle-class adult", hand-drawn illustrations of heads (top right) showing "Lower-middle-class adult" and Full-body hand-drawn illustrations (bottom right) as annotations to "Poor adult".

social class outcomes for 10,000 boys raised in five social classes—describing how Black boys are more likely to end in a poorer social class as adults compared to White boys. The original data story already included data about race and gender, using blue and yellow colors to represent Black men and White men respectively, presenting their life outcomes for five different social classes. We chose this visualization because it highlights a clear disparity between an underrepresented demographic group and a majority group, and thus a case where an awareness of racial equity can impact how viewers interpret the visualization.

In Figure 10, we use four of these five social class outcomes to illustrate different strategies for varying visual style. In the "Rich adult" category, we use circles with blue and yellow outlines that mirror the original data story, but with simulated skin tones based on our narrow Fenty Beauty mapping (tones in the 100s for White and only tones in the 400s for Black). Similarly, for the "Upper middle-class adult" category, we use geometric people with blue and yellow clothing and the same Fenty fills. For the "Lower middle-class category", we used illustrations of human heads from Open Peeps [49] (one of the few diverse and composable open-source collections of hand-drawn human characters) that encode physical diversity using Fenty skin tones and hand-selected hair colors/styles. The collection contains specifically-labelled hairstyles such as short twists and afros that are more closely associated with the Black category and we used those throughout with the Black category, while using short, straight and wavy hairstyles with the White category. Finally, the "Poor adult" category uses full-body Open Peeps illustrations [49] to annotate the original visualization. We use two illustrations, one representing a Black man and the second representing a White man, by varying skin color and hair style with clothing mirroring the original data story. For these last two social classes, we used hand-drawn illustrations in an attempt to explicitly convey a sense of the people behind the data.

Figure 11 shows a second re-creation of an existing data story from *The New York* Times titled "Why So Many Children of Immigrants Rise to the Top" [14]. The original story uses an interactive animation with 3D human models to contrast the social class outcomes of the children of immigrants against those of children whose parents were born in the US. The animation ends with a static visualization of aggregate colored dots showing the percentages of children of immigrants (green) and children with US born parents (orange) in five social classes. Unlike Figure 10, this data story does not contain gender and race information. In our re-creation, we chose to randomly simulate race and gender for the five social classes, using hand-drawn heads from the Open Peeps collection [49] and the Fitzpatrick skin tones introduced in Section 3.2.3. We chose the Fitzpatrick palette over the Fenty palette to prioritize physical details shown by the Open Peeps heads. Because of the artistic style of the Open Peeps heads and the

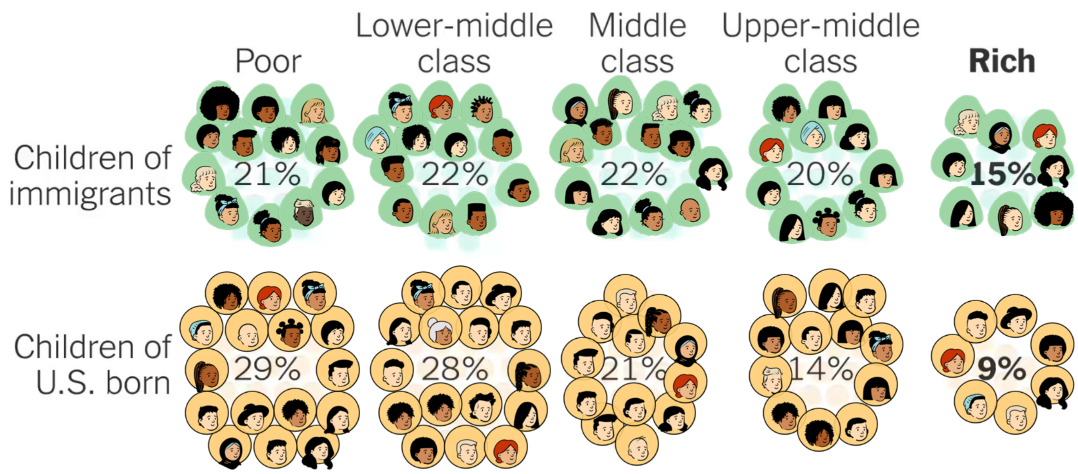

Figure 11: Using hand-drawn illustrations of heads from the Open Peeps collection to recreate a static visualization from “Why So Many Children of Immigrants Rise to the Top” by *The New York Times* [14]. This anthropographic uses randomly generated race and gender demographic data with the Fitzpatrick fills.

orange colors from the original data story, the Fitzpatrick palette was more visually distinct. We randomly assigned skin tones to each head and placed each on a bubble similar to those in the original data story. We selected hairstyles using a similar process as for the previous example, using existing labels for hairstyles from the Open Peeps collection [49] to represent men and women with distinct hairstyles.

These examples highlight the diverse range of ways in which simple demographically diverse anthropographics can be executed and incorporated into existing visualization archetypes. Our recreations of existing visualizations also foreground the role of designers who may hand-select visual encodings for diversity, rather than assigning them programmatically or randomly as in the previous examples. On one hand, relying on direct designer input transparently introduces opportunities for that designer’s biases or stereotypes to manifest in the encodings. Yet, such a framing may obscure the myriad of ways in which tools for more automated creation of demographically diverse anthropographics (and the designers who use them) need to be sensitive to biases, misconceptions, and harms. We discuss these challenges further in the following section.

4 CHALLENGES

Based on our initial experiences designing, comparing, and critiquing a variety of demographically diverse anthropographics, we also highlight several broad social and technical challenges related to their creation and use.

4.1 Demographic Categories are Social Constructions

Demographic categories in datasets typically do not reflect the underlying physical characteristics of the individuals they describe. Rather, they are social constructions that seek to bin diverse social groups into discrete classes or categories—often in ways that do not reflect real-world complexity and ambiguity, and which manifest historical and cultural biases [26].

For both historical and institutional reasons, these categories can often be narrow, archaic, and inconsistent. For example, one of the most comprehensive processes of collecting demographic data about populations are national censuses, administered by governments around the world. Thus, census demographic categories directly influence how other institutions treat demographics [8, 50]. Yet the process of grouping individuals into categories based on their individual or social characteristics has a deep rooted history in colonization and discrimination [9, 26]. As a result, demographic categories such as race and gender reported on most national censuses are restrictive when compared with how these categories are currently understood and used [43]. Likewise, demographic categories might fail to capture how individuals personally identify or might not align with how they externally represent [8, 50]. For example, current categories for gender might distinguish between “gender identity” and “gender expression” but the census might only use a single category for “sex”. Census demographic categories for race are also generally broad, with categories such as “Asian” that group individuals with a wide range of characteristics, lumping together individuals with geographical or national origins as diverse as “Chinese”, “Japanese”, and “Thai” while completely ignoring distinct regional, local, or community identities. These narrow demographic categories often do not account for the variations in physical characteristics between different demographic groups or within individual ones. Using physical characteristics to include or exclude individuals from broader or ambiguous demographic categories (like the “Two or More Races” category in the US census) can be even more challenging.

Moreover, categories and labels used across data sources may not be consistent or aligned with one another. In the US and Canada, for example, institutions like banks, universities, and healthcare providers often choose to use demographic categories that more closely align with individual identity [2]. However, for formal reporting and to ensure compliance with anti-discrimination laws, these institutions are still typically required to use more rigid census categories [11, 16, 38]. These inconsistencies can create challenges for designers, since two different demographic data sources can result in vastly different anthropographics depending on how they prioritize individual identity and interpret the census categories.

4.2 Lack of Accurate and Intersectional Demographic Data

Creating demographically diverse anthropographics from datasets can also be challenging because most data about people contains limited (or no) demographic information at all. Creating demographically diverse anthropographics for these datasets thus requires pairing them with other demographic information, either real or simulated. In some cases—particularly datasets with a regional or geopolitical component—designers can rely on large-scale demographic data from censuses and similar sources. However, often accurate demographic data for the specific sub-populations of interest simply does not exist. For example, demographic information for narrow groups like employees or students at a single institution may not be collected at all. Similarly, demographic information for transnational groups like refugee populations may be difficult to align with existing data. Real or simulated demographic data that does exist also tends to be aggregated rather than intersectional. This aggregation can mask correlations and relationships between categories (for example "race" and "religion") or within categories and lacks information necessary to accurately reproduce real individuals. As a result, demographically diverse anthropographics created using these datasets can exhibit inaccurate or implausible combinations of attributes not present in the real population, which might undercut the credibility of the visualization.

4.3 Encoding Demographic Categories as Visual Characteristics

Wide-ranging and representative data about important human physical characteristics like skin tone or invisible characteristics such as gender identity, disability, or religion (among others) generally do not exist. Similarly, reliable mappings between socially-constructed demographic categories like race or ethnicity and physical characteristics such as skin tones and hair type are challenging to collect due to variations in physical characteristics *within* demographic groups. Moreover, the data that does exist is often artificial or skewed towards specific populations, might consist of broad categories, or is aggregated for privacy. This poses real challenges for the creation of demographically diverse anthropographics, which fundamentally involve visually representing these characteristics.

For example, no systematic collections of values for attributes like human skin tones exist in the literature, and possible alternatives (such as the Fitzpatrick-inspired Unicode emoji modifiers [45, 51], databases of makeup shades [1], or tones extracted from photo datasets [15]) all exhibit systemic biases. Not only do they fail to reflect the range of real-world skin tones, they disproportionately count tones from privileged groups, reinforcing existing social and economic biases. For example, D'Ignazio and Klein note that the number of dark makeup shades is glaringly limited compared to the number of lighter shades [1, 17] in ways that reflect historical beauty norms and the economics of the skin care industry rather than the real-world distribution of skin tones (although recent inclusive collections like the Fenty Beauty shades we sample have sought to address this). Analogous challenges are present across a wide range of physical and anatomical characteristics including hair color and texture, facial features, and body shapes, as well as cultural mappings manifest in clothing and accessories. Similarly, existing demographic data categories about disability are often focused on identifying visible disabilities and might exclude individuals with invisible disabilities such as chronic disease or mental illness [8, 50]. Even existing collections of hand-drawn illustrations of demographically diverse individuals are still severely limited with regard to the invisible disabilities they can be used to portray. Data about other demographics such as religious affiliation is also harder to illustrate via physical characteristics.

In the absence of reliable mappings between demographic data and physical or invisible characteristics, designers can face uncomfortable or problematic choices. (For example—"which skin tone(s) to use for a given ethnicity?") In these cases, designers may have to rely on their own assumptions about the appearances of the individuals in particular demographic groups—which can result in both conscious and unconscious stereotypes or caricatures. For instance, mapping Unicode emoji skin tones to specific racial categories (as we examined in Section 3.2.3) can be problematic as it hides differences in skin tone diversity *within* racial categories and relies on the designer's assumptions about the skin tones of individuals in these categories. Research in psychology has documented biases such as "own-race bias" which indicate that individuals are more likely to remember faces with features similar to their own demographic group [22]. Similarly, designers may be less likely to accurately represent the physical characteristics of individuals from outside their own communities. Robertson et al. [45] allude to this bias when describing inaccuracies in the foot emoji released by Apple, in which the sole of the foot grows progressively darker along with the base skin tone. This representation is dermatologically inaccurate and does not reflect the typical appearance of people with more strongly melanated skin. However, the discrepancy was not caught by the designers—who likely did not belong to those demographic groups.

Other potentially problematic choices might arise if designers are unaware of the cultural associations of specific physical characteristics with certain demographic groups. This can be an issue if designers are using existing anthropographic illustrations which they did not personally design. The Open Peeps image collection [49], for example, contains specific hairstyles such as Afros, Bantu knots, twists, and braids that are typically associated with and are culturally significant for individuals identifying as Black, but different hairstyles can also have different associations in other global communities. Without this knowledge, a designer using these hairstyles to represent individuals from other racial categories might create inaccurate and potentially insensitive anthropographics.

An awareness of these nuances is also useful when designers are creating their own anthropographic designs. For example, designers need to be conscious of the risks of ableism and tokenism when creating graphics that represent disabilities, and should consider the potential for ageism when using facial features as markers for age. Similarly, when encoding invisible characteristics such as religious affiliation or invisible disabilities, designers might choose to represent these using accessories that might be familiar to viewers and signal the presence of these invisible characteristics. However, since these accessories would not be genuine attributes of the original datasets and would have to be generated separately, designers need to be aware of their cultural subtext to avoid potentially offensive misrepresentations.

4.4 Avoiding Unintended Defaults

Given the challenges associated with creating demographically diverse encodings, most current anthropographics represent people using "default" or generic human shapes. More generally, designers of demographically diverse anthropographics may also be tempted to rely on default shapes, colors, or other visual features in cases where they lack good demographic mappings. However, prior research suggests that "default" human representations, even relatively simple ones, tend to carry implicit cultural markers and may unintentionally exclude marginalized communities [41, 45].

In the context of video games, Passmore and Mandryk observed that players from marginalized communities often encounter few characters that look like them or which they can closely identify with [41]. Despite customization options, players reported that default character models frequently had typically White physical features and that additional diversity characteristics, such as hair and skin color, when layered on the default design, resulted in inaccurate and unrealistic depictions of diversity [41]. These default forms signaled to players from marginalized groups that diversity was an afterthought, likely due to unconscious biases held by game developers [41]. Similarly, Robertson et al.'s examination of emoji skin tone modifiers suggests that marginalized communities typically assume default designs, such as the yellow finger emoji, to be White [45], whereas emojis with skin-tone modifiers are mostly associated with non-White individuals. In this context, designers creating anthropographics also need to be sensitive to the implicit demographic signals sent by even simple or generic human shapes.

4.5 Explaining Demographically Diverse Anthropographics to Viewers

Because visualizations encode data, they can carry an assumption that any visual encoding used in them is data-driven. As a result, viewers may assume that the physical and demographic characteristics of individuals in anthropographics should be interpreted as part of the original dataset even if they are not. More granular and realistic anthropographics can also create opportunities for misunderstanding and even raise privacy concerns, suggesting that data corresponds to distinct real-world individuals even when characters are actually composites or use simulated characteristics.

These issues suggest that designers creating demographically diverse anthropographics need to consider how to more explicitly surface information about these encoding choices to viewers. Such explanations can take a variety of forms, including leveraging narrative techniques to explain demographic encodings when introducing a visualization for the first time, providing context for the encodings via text or annotations alongside the visualization, or allowing viewers to directly inspect individuals marks in the visualization to reveal their provenance.

5 RESEARCH OPPORTUNITIES FOR DIVERSE ANTHROPOGRAPHICS

At this point, much remains unknown about the design and utility of demographically diverse anthropographics. With that in mind, considerable additional research is necessary to characterize the extent to which surfacing demographic diversity in anthropographics changes the ways in which people experience and interpret them. More work is needed to support the development of demographically diverse anthropographics—including approaches for creating robust visual mappings of diversity characteristics and tools for authoring visualizations that use them. Doing so creates opportunities for reflective and critical approaches to visualization, as well as the inclusion of traditionally marginalized groups.

5.1 Understanding the Impact of Anthropographics

Although previous research on anthropographics has focused on using these visualizations to elicit empathy, anthropographics have the potential to be used in a variety of other contexts, including for data-driven storytelling [31], demographic reporting at institutions [16, 38], raising awareness about social issues [7, 25, 36], and in decision-making processes [2]. This breadth of applications calls for research that more systematically examines potential benefits of anthropographics beyond just eliciting empathy, and considers the wider range of affective intents found in communication-oriented visualization (as documented in Lee-Robbins and Adar's recent taxonomy [29]). For instance, potential positive applications of anthropographics could include belief elicitation [33] related to demographic data of marginalized populations—particularly dispelling stereotypes of marginalization and highlighting positive stories such as educational, social and political achievements through data storytelling [31]. Research communities working on creating anti-racist educational tools to address implicit biases about marginalized populations might also benefit from data visualizations that show demographic diversity. Similarly, diverse anthropographics could be useful for combatting misinformation on potentially contentious topics such as public policy, immigration, and voting behavior.

Conversely, Holder and Xiong [24] have shown that hiding demographic variability in visualizations potentially leads to unintended effects such as stereotyping and deficit-thinking from viewers. Replicating or extending these studies using attributes like skin tones and other demographic diversity characteristics could provide additional insight into whether diverse anthropographics might mitigate these effects. Conducting both detailed qualitative studies and large-scale crowdsourced evaluations with individuals from diverse backgrounds may also be useful for understanding how viewers perceive generic human shapes in current homogeneous anthropographics as well as physical characteristics such as skin tones in diverse anthropographics. Such work could also investigate the effects, if any, of increasing realism and encoding demographic diversity via physical characteristics.

5.2 Representing Marginalized and Underrepresented Populations

Designing diverse anthropographics is fundamentally about surfacing human diversity and revealing the presence of individuals and groups in data—with a strong emphasis on people who have traditionally been marginalized and underrepresented. Yet, the communities of designers, researchers, and other practitioners creating these kinds of graphics are typically less diverse [32]. Representing marginalized populations in anthropographics will require that researchers be aware of nuances in agency, ownership, and allyship [30] and how these factors influence whether underrepresented populations choose to actively or passively participate in this work. To support active participation, researchers might develop visualization interfaces that facilitate direct feedback and other contributions from underrepresented groups. For example, Schwan et al. [47] propose embedding disclosure strategies from critical-feminist practice into visual data storytelling interfaces to show contextual information. These kinds of disclosure frameworks may also be useful when authoring diverse anthropographics, giving designers ways of surfacing the rationale behind sensitive encoding choices. Underrepresented populations might also use these tools to provide active feedback and resist inaccurate or harmful misrepresentations.

Indeed, anthropographics that designers think are diverse can still hide differences in lived experiences and demographics, especially when viewed from the perspective of marginalized populations. Given the limitations of existing collections like Open Peeps [49], additional work is necessary to create collections of assets and approaches that can more reliably reflect diverse experiences. Participatory design approaches, like inviting members of marginalized populations to critique existing designs and author more diverse representations using existing character creation tools, show some promise here [41]—but also highlight the limitations and preconceptions baked into many of these platforms.

Researchers and designers will also need to critically reflect on whether their work with marginalized populations is extractive or is replicating existing systems of oppression that can further harm these populations. Notably, because data about marginalized populations may be incomplete or require special considerations for privacy and anonymity—demographic data and other contextualizing information about these groups is often sparse. Meanwhile, the data that *is* available about marginalized populations (including groups like refugees, unhoused people, or abuse victims) often focuses exclusively on the issues affecting them—such as conflicts, death, and suffering. If designers and researchers are unaware of these considerations, this can result in visualizations that repeatedly and exclusively focus on marginalized groups through the lens of victimhood. To address these concerns, we call for more research that surveys the range of anthropographic projects that marginalized populations have been included in to date. Finally, we advocate for more work to support designers and researchers in navigating the various tensions when working with marginalized populations (as detailed by Liang et al. [30]).

5.3 Supporting Good Visual Mappings of Diversity

The process of creating demographically diverse anthropographics requires realistic, representative, and intersectional mappings between demographic data and visual characteristics. Given the limited availability of this kind of data, we call for more research focused on creating equitable datasets for inclusive visual representations of demographic data and on safeguarding these datasets from misuse. We are also mindful that ethically and accurately creating these datasets will be challenging and requires the consent of the populations whose data is being collected.

For example, collecting distributions of skin tones by country by using geotagged photographs from social media could support designers wishing to create demographically diverse visualizations from data with "nationality" or "country" categories. Alternatively, researchers could collect mappings between demographic attributes and physical characteristics by asking participants on crowdsourcing or data journalism platforms to select skin tones or construct avatars that reflect their own self-identified demographic data. However, these kinds of collection approaches run the risk of oversampling already-advantaged groups and are likely to exhibit biases and inconsistencies based on cultural and socioeconomic factors that will differ across communities and populations.

Collecting these kinds of mappings are also not without risk, since the collection of personal and demographic information in any context introduces opportunities for bias and abuse. Moreover, such datasets have the potential to be used in ways that are questionable and which serve problematic agendas. For example, as Jablonski points out, the earliest datasets classifying individuals by skin color by Linnaeus were used to define social hierarchies that were eventually used to justify racism and colonization [26]. Re-creating such datasets today has the potential for related kinds of misuse. Care needs to be taken to protect the privacy and agency of individuals who contribute to these kinds of efforts.

5.4 Enabling the Creation of Demographically Diverse Anthropographics

The creation of diverse anthropographics requires datasets and designs that reflect the physical diversity of people. Our work is a first step towards conceptualizing the creation of demographically diverse anthropographics. However, we recognize that the creation of human-shaped visualizations with physical characteristics will likely be an intensive process. For instance, openly hosting collections of existing anthropographics from data journalism and research studies can allow readers, designers, and researchers to directly contribute to these collections by adding new content, modifying or providing input on existing designs. Future tools for creating diverse anthropographics may also be able to leverage image synthesis techniques from machine learning and computer vision research to create more realistic anthropographics. In particular, AI image-synthesis platforms such as DALL-E 2 [44], AI-augmented illustration tools [19], and text-to-image synthesis tools [20] are likely to lower barriers for creating large numbers of unique human images that can be used to represent individuals. Designers creating diverse anthropographics may also be able to leverage techniques such as visual style transfer, as demonstrated by Shi and colleagues [48]. While promising, considerable research is necessary to address the various drawbacks associated with these techniques, including addressing inherent biases in these tools. We also call for the development of unit visualization tools that incorporate anthropographics along with standard visualizations to allow for more flexibility in analysis, building upon recent unit visualization tools such as ATOM [40].

The design of demographically diverse anthropographics is fundamentally about incorporating good visual mappings that equitably represent the people behind the data. With that in mind, we call for more efforts to raise designers' and developers' awareness of problematic or inaccurate demographic encodings, and encourage thoughtful and humane visualization design choices.

6 CONCLUSION

In this work, we have explored a variety of approaches for creating demographically diverse anthropographics—focusing in particular on representing human diversity via physical characteristics, while varying the visual style and the types of data used. Our goal was to surface approaches for designing diverse anthropographics with an awareness of racial equity [46], taking inspiration from critical design practices such as data feminism [17] and critical information visualization [18]. However, we emphasize that our approaches are not neutral, have limitations, and are not meant to be prescriptive. Instead, they represent just a few of the plurality of approaches for creating diverse anthropographics. Our artifacts and reflections foreground a number of technical and social challenges regarding the creation of these designs, and emphasize that representing human diversity in visualizations remains a double-edged sword. As a result, navigating the tensions between a lack of available resources, the benefits of inclusive representations, and the potential of harmful ones mean that the barriers to creating demographically diverse anthropographics remain high—particularly when those demographics are linked to marginalization.

At the same time, creating more humanizing representations of data remains an important challenge for visualization research, and one that impacts both analysis and communication. Despite these challenges, we are hopeful that the research opportunities we propose can enable day-to-day adoption of visualization strategies that more deeply humanize people behind datasets. We believe that more inclusive visualization practices like these may also offer new opportunities for traditionally marginalized groups to play a role in visualization research. With that in mind, we hope that this work—and in particular our research opportunities for diverse anthropographics—can start new discussions, raise new questions, and provoke greater consideration of how visualizations can truly *represent* people.

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