Collecting and Reporting Race and Ethnicity Data in HCI

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ABSTRACT

Engaging racially and ethnically diverse participants in Human-Computer Interaction (HCI) research is critical for creating safe, inclusive, and equitable technology. However, it remains unclear why and how HCI researchers collect study participants' race and ethnicity. Through a systematic literature analysis of 2016–2021 CHI proceedings and a survey with 15 authors who published in these proceedings, we found that reporting race and ethnicity of participants is uncommon and that HCI researchers are far from consensus on the collection and analysis of this data. Because a majority (>90%) of the articles that report participants' race and ethnicity are conducted in the United States, we focused our discussion on race and ethnicity accordingly. In future work, we plan to investigate considerations and best practices for collecting and analyzing race and ethnicity data in a global context.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Social and professional topics** → *Race and ethnicity*.

KEYWORDS

race, ethnicity, systematic literature review, HCI research, survey

1 INTRODUCTION

As identities of study participants have proven to influence the uptake, experience, and benefits of technologies, the Human-Computer Interaction (HCI) community has made considerable efforts towards inclusive and diverse research practices over the past few years [1, 7, 11, 16, 42, 43, 47]. For instance, gender HCI has emerged as a mature subfield of HCI that focuses on variations in how people

of different genders interact with technology [46]. As another example, HCI for development is a growing subfield that considers how designs and technologies interact with the under-resourced and economically disadvantaged communities [48, 51]. In this work, we focus on one such diversity dimension — race and ethnicity of participants in HCI — which has remained relatively under-explored in current research. In 2017, Schlesinger et al. [42] found that less than 0.1% of the papers in the CHI proceedings between 1981 and 2016 engaged meaningfully with race, compared to 0.2% and 0.6% for gender and socioeconomic class, respectively. Similar findings were reported on the basis of a quantitative content analysis of accepted papers in CHI 2006, 2011, and 2016 [16]. The authors highlighted the importance of intersectionality (i.e., an identity framework that seeks to understand the complexity of multiple, overlapping, intersecting social identities [8, 39]) when examining the composition of the participants in HCI research. In particular, they emphasized that HCI researchers should take an interest in understanding how various dimensions of participants' identities (e.g., race, gender, socioeconomic status) interact with each other, and provide recommendations for deeper engagements with the resulting complex identities.

Other research has explored the issue of race, ethnicity, and bias in HCI research and the HCI community via a critical race theory lens [33, 44]. Ogbonnaya-Ogburu et al. [33] argued that racism is pervasive in social-technical systems and implored that HCI research should be attuned to the issue of race; they suggested that participation of under-represented minorities must be sought after in *all* research activities. Concerted efforts among HCI researchers also led to a workshop titled "engaging in race in HCI" in CHI 2020 that aimed to identify better practices for engaging with race and improving racial inclusiveness and equity in HCI [44]. This workshop allowed the HCI community to begin assembling recommendations for like-minded researchers to discuss the role and implication of race in HCI, which ultimately led to a series of zines featuring race and inclusiveness in HCI research [37].

Of course, the topic of collecting and reporting race is not unique to HCI. For instance, in medical sciences, the American Medical Association (AMA) Manual of Style states that "specifying the race or ethnicity of study participants can provide information about the *generalizability of the results of a specific study*"; therefore, it recommends reporting aggregate race and ethnicity for *all* study participants [12]. The American Psychological Association (APA) [2] has made similar suggestions for empirical studies in psychology. However, given the breadth of research interests and methodologies of

HCI, we should neither copy nor ignore existing recommendations from other disciplines.

When put together, the existing work calls for a deeper understanding of the current practice on reporting race in HCI research. Therefore, our work makes strides towards this goal by answering the following research questions:

RQ1: Who are the study participants in HCI and when are their race and ethnicity information reported?

RQ2: What are some considerations that speak for and against collecting this information?

By answering the two research questions (primarily in the context of race and ethnicity in the United States (U.S.)), we make the following contributions to the literature:

- We provide an empirical analysis of the frequency of reporting CHI participants' race and ethnicity, showing that less than 3% of CHI papers in the past six proceedings have included such information.
- Through a survey with selected authors who published in CHI, we summarize the motivations for and against reporting race and ethnicity in HCI research.

2 RELATED WORK

Our work is motivated by both the practice of racial data collection outside of HCI and the growing efforts to improve the collection of related demographic variables such as gender [32, 41, 45] within HCI. In this section, we first briefly review the racial categorization in the U.S., which provides the foundation for our quantitative analysis. Furthermore, we provide a selective overview of the practices for collecting and analyzing racial data in several research disciplines. We end the section by sketching how those approaches might inspire parallel efforts towards racial data in HCI.

2.1 Racial categorization in the U.S.

Racial categories have been included on every U.S. census since 1790, and the history of U.S. census reveals the complexity of racial and ethnic data collection [36]. Firstly, prior to the 1960 census, an individual's race was determined by census enumerators, rather than through self-report. Moreover, categories used in census changed almost every decade to reflect the politics and societal values at the time. For instance, "Native Hawaiian or Other Pacific Islander" was historically grouped with Asians, and only became a new category since 2000. "Mexicans" were counted as a racial category in 1930, but as that category has since disappeared, many resort to the "other race" option and have been grouped under the Hispanics ethnicity only. The ability to identify as multi-racial was only won through extensive advocacy in 2000 [53]. Racial categorization has always been extremely political, and the miscategorization and undercount of people from racial minority groups has contributed to systemic oppression and exclusions [4].

U.S.-based researchers may be familiar with the standards published by the U.S. Office of Management and Budget (OMB) in 1997, which mandates minimum standards for collecting and presenting data on race and ethnicity for all federal purposes. The OMB standards have two categories for ethnicity (Hispanic versus non-Hispanic) and five categories for racial data at minimum — White, Black or African American, American Indian or Alaska Native, Asian, and Native Hawaiian or Other Pacific Islander. The OMB standards have been the guideline for collecting and presenting data on race and ethnicity for *all federal reporting*, including the decennial census and the mandates by U.S. grant funding agencies such as the National Institutes of Health (NIH) and the National Science Foundation (NSF) [30, 31].

2.2 Collection and analysis of racial data in research

Here, we look at how social, medical, and computer sciences have approached racial data as comparative case studies.

Social science scholars have long acknowledged the role of race in shaping individuals' social status and everyday life experience [5, 14, 14, 25]. However, there is less consensus on whether the field should use racial classifications to assess the role and consequences of race. Some argue that collecting and reporting data on race and ethnicity would promote racial division and further the status quo of racial discrimination, while others take a "what we cannot measure, we cannot understand" approach, and continue to report observed racial differences from profiling in law enforcement to disparity in healthcare systems. In 2003, the American Sociological Association (ASA) issued a statement in support of continual collection and research of data on race [3]. Their reasoning is summarized as follows: (i) racial identities are central to societal organization and relationships, and therefore the very core of social science research; (ii) taking a "color-blind" approach and ignoring participants' race in research does not eliminate the use of racial categories and racism in everyday life and, consequently, the impact on societal outcomes; and (iii) understanding the role of race is central to challenging the existing systems of racial discrimination and stratification.

In contrast to the debates over racial data collection in social sciences, race and ethnicity of study participants are widely collected and used in healthcare databases to ascertain important group-level differences in healthcare outcomes in the U.S. [22, 34]. Despite this established practice, the basis of the observed race-associated differences in healthcare outcomes remains under-explored. Jones [19] argued that as a social construct, race only serves as a very rough proxy for variables of interest such as social class and culture. Instead, race appears predictive of healthcare outcomes because of the *racism* that has operated throughout the U.S. history and to date. As an example, an analysis by Jones et al. [20] demonstrated that being classified by others as "White" is associated with better health status, *regardless of one's self-identification*. In view of the complex interpretation of "race", multiple threads of work have urged researchers in public health to take an interest in elucidating the underlying causes of the observed differences across race and ethnicity groups, e.g., by generating hypotheses about the basis and designing data collection and analysis plans to test the hypotheses. For instance, the difference in rates of estrogen-receptor-negative breast cancer between Black and White women in the U.S. is well-documented. Building on this observation, Krieger et al. [24] demonstrated that being born in the states that practiced Jim Crow laws (i.e., legal racial segregation) is associated with higher odds of cancer, thereby attributing the observed differences to racially discriminating laws.

Within HCI, several authors have argued, through qualitative, mixed-methods, or quantitative methods, that there is a general

lack of meaningful engagement with race and ethnicity [16, 33, 37, 42]. However, the current practice, as well as the motivations, for collecting and reporting study participants' race and ethnicity remains under-explored. In this work, we analyzed recent CHI proceedings to understand the existing practice. Furthermore, we also surveyed authors to identify the motivations and methods for collecting racial and ethnic data of their participants. In future work, we hope to curate a list of considerations and "best practices" on collecting race and ethnicity data (similar to those on the gender of study participants [32, 41, 45]) for HCI researchers.

3 METHOD

To answer our research questions, we conducted a systematic literature analysis of the published papers in the most recent six CHI proceedings from 2016 to 2021 and followed up with a survey to the authors whose papers reported race and ethnicity data of their participants in this time period. The restriction on time is motivated by (i) the goal to understand the *current practice* on collecting racial and ethnic data of study participants, and (ii) the observation that older literature rarely reports this information [16].

3.1 Dataset curation

We started with a total of 3,910 research articles published in the most recent six proceedings of CHI on ACM digital library and proceeded with a keyword-search method informed by prior work [16, 42]. We initially filtered the collection using the keywords "race" OR "racial" OR "ethnicity", which narrowed down the corpus to 663 articles. We then experimented with adding potentially defining keywords (race/racial, ethnicity/ethnic, White/Caucasian, African American/Black, Asian, Hispanic, Native American/American Indian, Pacific Islanders), and sampled the first 10 articles returned in each year to judge the quality of our search (the quality here is defined to be the number of search results that contained detailed race and ethnicity information of the study participants). The final keyword set that yielded most relevant articles empirically is (i) "race" OR "racial" OR "ethnicity" AND (ii) "Hispanic" OR "African American" OR "Asian" OR "Caucasian". After identifying this initial collection of 340 articles, we then checked for the racial and ethnic composition of study participants in each article manually. Next, we aggregated the racial and ethnic information of study participants over all articles that detailed this information. Because of the focus on the race and ethnicity in the U.S. context for this work, we further limit the corpus to those articles whose authors had U.S. affiliations *or* whose participants were recruited in the U.S. We display the corpus curation process in Figure 3 of the Appendix.

For reference, we obtained racial and ethnic composition from two additional sources: (i) the 2015–2019 demographics estimates of the U.S. collected by the United States Census Bureau [49]; and (ii) the 2015–2019 demographics estimates of U.S.-based drug trials collected by the U.S. Food and Drug Administration (FDA) [6].

3.2 Dataset analysis

As stated in Section 2.1, categorization of race and ethnicity is extremely complex. In this paper, as a proof of concept, we adopted the following procedures to group the race and ethnicity categories across different studies. Firstly, we made the simplifying assumption that the racial categories reported by studies in our final corpus refers to the non-Hispanic subset (e.g., reported White participants are non-Hispanic Whites). This is because all studies in the final corpus are U.S.-based, and many collected race and ethnicity using one single question. As a result, data was reported for a separate "Hispanic" group, regardless of participants' racial identification. Secondly, we aggregated the participants into the following categories that roughly align with the OMB standards: White, Black or African American, Asian, and Others (including American Indian and Alaska Native, Mixed races, Native Hawaiian and Other Pacific Islander). This choice of analysis is largely driven by reported racial categories in papers published in CHI, which certainly does not capture the full complexity of race and ethnicity of the study participants, even in the context of the U.S.

In addition to the aggregate analysis of studies, we also report the following statistics of interest: (i) the number of studies that collected ethnicity separately from race, and (ii) stratified analysis of racial and ethnic breakdown of large (>100 participants) studies versus small-to-medium-scale studies (≤ 100 participants).

3.3 Survey

While all papers in our final corpus reported their participants' race and ethnicity, many in the final corpus left the *reason and process* of collecting the race and ethnicity of their participants *implicit*. We therefore conducted an additional survey to find out why researchers collect racial and ethnic data, and to learn about potential challenges they may have experienced. For each publication in the final curated corpus, we emailed the first and senior authors with a list of open-ended questions on why they collected race and ethnicity information of their participants.

In addition to the responses from the authors, we note that some authors already highlighted the importance of considering race and ethnicity for the piece of technology under study as part of their discussion sections. For instance, research on virtual reality and gaming made up a substantial portion of the corpus: by surveying gamers from a diverse race and ethnicity background, Passmore et al. [35] established "*significant differences between players of color and White players on perception of racial norms in gaming, effects of behavior, emotions, player satisfaction, engagement, and beliefs stemming from a lack of diversity.*" Moreover, they emphasized that the diverse recruitment amounted to "*higher dissatisfaction [in diversity in digital games] than previous research.*"

4 RESULT

4.1 RQ1: Who are the study participants in the curated CHI corpus?

In total, we analyzed 340 manuscripts, of which 93 (27.3%) provided descriptive statistics on the racial and ethnic breakdown of their study participants. Our analysis showed that only 93 (2.4%) of 3,910 CHI papers included descriptive information of participants' race and ethnicity. This is likely an undercount given that the final corpus only included studies with the specified keywords.

Out of the 93 manuscripts, the median number of reported racial and ethnic groups is 4 (IQR: 3–5). Only a small number (17; 18.2%) of studies mentioned (or was inferred of) using two separate questions

for race and ethnicity. The median number of participants of the studies in the final corpus is 28 (IQR: 18–187); the largest study reported the racial and ethnic breakdown of 2,041 participants [50], and the smallest study in our corpus had only six participants [15].

The aggregated studies reported 19,684 participants in total, 12,627 (64.1%) of whom are non-Hispanic White; 2,028 (10.3%) Black; 1,766 (8.9%) Hispanic; 1,327 (6.7%) Asian; and 1,939 (4.6%) Others (with 205 Mixed races and 98 American Indian or Alaska Natives). By contrast, according to the estimated demographic data by the U.S. census for 2015–2019, 60.7% of the population in the U.S. is non-Hispanic White; 12.3% Black; 18% Hispanic; 5.5% Asian; and 3.5% Others (2.4% Mixed and 0.7% American Indian or Alaska Natives). Regarding the U.S.-based FDA drug trials during 2015 and 2019, non-Hispanic White accounted for 64.5% of the participants, followed by 16% for Black and 15% for Hispanic. Asians and Other groups account for 2% and 3.5% of the trial participants, respectively.

Racial and ethnic compositions from the three different sources (CHI, U.S. Census, and the FDA drug trials) are displayed in Figure 1. We see that compared to the U.S. Census, CHI studies in our final corpus have slightly more non-Hispanic Whites and slightly less Hispanics. In addition, Figure 1 suggests that participants in neither CHI studies nor FDA trials are representative of the aggregated U.S. demographics. However, we note that many CHI studies actively recruited a representative sample of their interest, which may or may not agree with the aggregated demographics of the U.S. For instance, Lopez et al. [27] was a non-Hispanic-White-focused studies, and Dosono and Semaan [10] specifically looked at the engagement and dynamics of the Asian American and Pacific Islander online communities. As a result, neither studies resembles the U.S. demographics by design, rather than by omission.

We also looked at longitudinal trend of the compositions of reported racial and ethnic groups across the six years of CHI proceedings. Overall, the racial and ethnic compositions of study participants appear stable over the course of six years, with a more noticeable increase of non-White participants from 2020 onwards. Figure 2 displays the racial and ethnic composition over the six years, stratified by the size of the study, where a study is classified as "large" if it has more than 100 participants and "small-to-medium" otherwise. We see that large-scale studies tend to have more White participants. This is partly due to the use of online platforms (e.g., Twitter or Mechanical Turk) for participant recruitment, which has been known to skew towards White samples [26, 52]. On the other hand, small-to-medium studies are more likely to target specific populations of interest (e.g., studying particular technology of interest in low-income neighbourhoods or among Black females). As a result, small-to-medium studies might appear more racially and ethnically diverse than larger studies.

4.2 RQ2: Why are race and ethnicity of study participants collected in the curated CHI corpus?

Almost all of the authors in our final corpus and survey sample were affiliated with an U.S. institution at the time of writing. Responses to our survey (n = 15) are summarized in Table 1. Because the authors could list multiple options in their open-ended responses, frequencies of the categories add up to over 15.
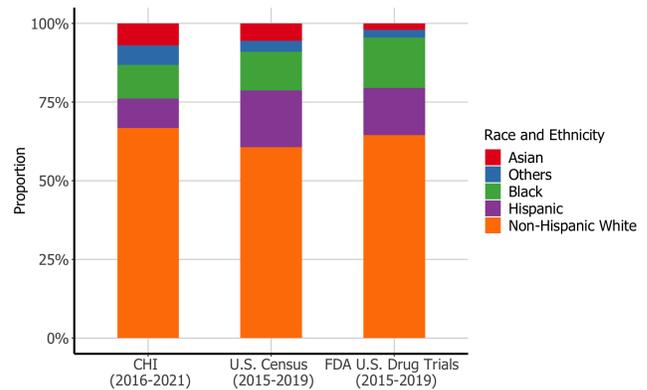

Figure 1: Racial and ethnic compositions of participants (in five groups) from three different sources: CHI proceedings (2016–2021, leftmost); demographics projection of the U.S. census (2015–2019, middle); participants of U.S.-based FDA drug trials (2015–2019, rightmost).
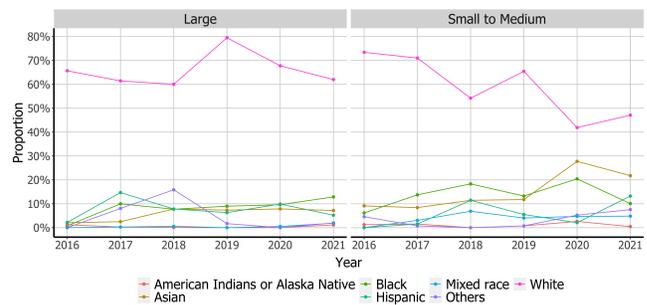

Figure 2: Racial and ethnic compositions of study participants from CHI proceedings between 2016 and 2021, by year and study size (large, >100 participants; small-to-medium, ≤ 100 participants).

	Occurrence
Why	
External validity	8
Targeted studies	4
Motivated by prior work	8
External requirement	2
Motivate future studies	4

Table 1: A summary of surveyed authors' responses. Note that multiple reasons and sources are allowed. Therefore, occurrences in each individual category could add up to more than 15. The categories are determined through a qualitative coding of the responses.

The most common reason ("Why" in Table 1) for collecting and reporting racial and ethnic information is *external validity*, that is, the degree to which the conclusion in one study would hold for other persons in other places and times [13]. For instance, one surveyed researcher noted in their response that "*If my data is really only from a sample of White people, then I need to acknowledge that as a limitation of the study and ensure that my analysis is contextualized in that particular identity*." A majority of the surveyed researchers also named prior work as a driving factor. As an example, one response noted that "*We were specifically interested in experiences of intra-community marginalization, which includes systemic biases such as racism*, and we wanted to ensure that our sample could capture such dynamics." In addition, the interplay between race, racism, and socioeconomic class in the U.S. motivates some researchers to "always collect these data" because when it comes to disparities as they affect technology, "*race and income are so woefully correlated in this country [the U.S.] (and others) — it was important to collect racial/ethnic information*." Only two out of 15 responses mentioned "external requirement" as the primary reason for collecting and reporting participants' race and ethnicity. Nonetheless, one response stated that "*I was in a Biomedical Informatics program, and health studies often have people collect this data (perhaps tied to NIH funding requirements)*", which speaks to the possibility of leveraging training from related disciplines to improve the collection and report of race in HCI.

5 DISCUSSION

The primary goal of our work is to understand the race and ethnicity data in HCI from the following aspects: (i) *who* are the HCI study participants in terms of race and ethnicity (RQ1); and (ii) *why* are race and ethnicity collected (RQ2). In terms of "who", our analysis revealed that, for studies published in CHI between 2016 and 2021, less than 3% included detailed race and ethnicity information about their study participants. Among those studies that are based in the United States, about 64% of total participants identified as non-Hispanic White. By contrast, 9% and 10% identified as Hispanic and non-Hispanic Black, respectively. Regarding "why", we found that for many of our participants (i.e., authors whose publications detailed race and ethnicity of their research participants), the theme of their work has a deep connection to race and ethnicity, which makes the racial and ethnic diversity of their participants an integral part of their studies. Other motivating factors to collect this information are to increase a study's external validity, achieve a more representative sample, or allow future research.

Our study is also subject to several limitations. One limitation is the scope of the discussion of race and ethnicity: the paper and existing work surveyed within are based on the racial and ethnic context of the United States. In part, this is due to the vast collection of existing research on race and ethnicity in the U.S. Moreover, given the high research output of U.S.-based HCI researchers, we hope that our work will serve as a proof-of-concept for future conversations about race and ethnicity in HCI studies more globally.

In terms of research methodology, our sampling could be subject to selection bias — published papers in CHI proceedings are a small subset of the broader HCI research outputs, and limiting publications to the past six years also potentially confounds our

finding with the longitudinal trend of research in race and ethnicity in HCI. For instance, more recent research outputs might have more discourse on race and ethnicity [16]. Our approach to corpus curation can also lead to an undercount: there is an array of excellent work in CHI that discuss racial and ethnic information qualitatively, and therefore do not provide racial and ethnic breakdown of participants. Such work is likely to be omitted in our curation process, despite the relevance. Furthermore, as the primary intention of this work was to start a discussion on race and ethnicity data collection, we did not prioritize an exhaustive, iterative refining of our corpus. Therefore, the reported results on the final corpus of papers are likely an underestimate of the CHI publications that collected and reported participants' race and ethnic information. Moreover, regarding the survey results, the 15 researchers who provided prompt responses to our inquiries might not be a representative sample of HCI researchers. For instance, 47% of the researchers who participated in our survey used separate questions to collect race and ethnicity, as opposed to less than 20% of the researchers in the entire final corpus.

6 CONCLUSION AND FUTURE WORK

As HCI continues to engage with a racially- and ethnically-diverse population of users, understanding the current practice of collecting race and ethnicity of participants in HCI research takes on high importance. Through a systematic review of published CHI papers and follow-up surveys with selected authors, we found that few published papers collected and reported their participants' race and ethnicity. Among those authors who did collect this information, the primary motivations include (i) strengthening the external validity of the study, and (ii) addressing the established disparities in the uptake and use of technologies between different racial groups.

Our findings reveal several important directions of future work. Firstly, CHI is a global community and reporting on the ethnicity of participants outside of the U.S. has been steadily increasing (e.g., David Bowman et al. [9], Koushki et al. [23], Randhawa et al. [38]). Extending our discussions to a more global context will champion the call for inclusiveness and representation of non-Western samples in the HCI research community. In addition, even in the U.S. context, the nuance of racial groups are not necessarily captured by the established categories used in the U.S. census. For instance, although Middle Eastern and North African Americans are classified as White in the U.S. census, a sizable number believe that they are not treated or perceived as Whites, and that such classification might perpetuate further harm [28, 29, 40]. Moreover, depending on the nature of the study, categories used in the U.S. Census such as Asian Americans and Pacific Islanders do not necessarily capture the underlying diversity of the group, and researchers have called for more granular categories to reflect and communicate participants' identities [17, 18, 21].

Another avenue of research is to investigate the challenges encountered in decisions around race and ethnicity data collection and analysis, especially among the researchers who decided *not* to collect and report such data. For instance, a systematic summary of the primary barriers (e.g., privacy and legal concerns, lack of systematic categories for large-scale international studies) could

inform future efforts on providing resources and designing tools to overcome these barriers.

Finally, in future work, we plan to outline a few recommendations which will serve to further the conversations on whether the data on race and ethnicity should be collected, and in what circumstances. Critically, we want to highlight the importance of a deeper and broader consideration of racial and ethnic data collection and analysis in HCI, and certainly within the research team — as long as racial and ethnic categories continue to govern social, political, and cultural interactions, collecting and analyzing racial and ethnic data fits squarely within the agenda of HCI.

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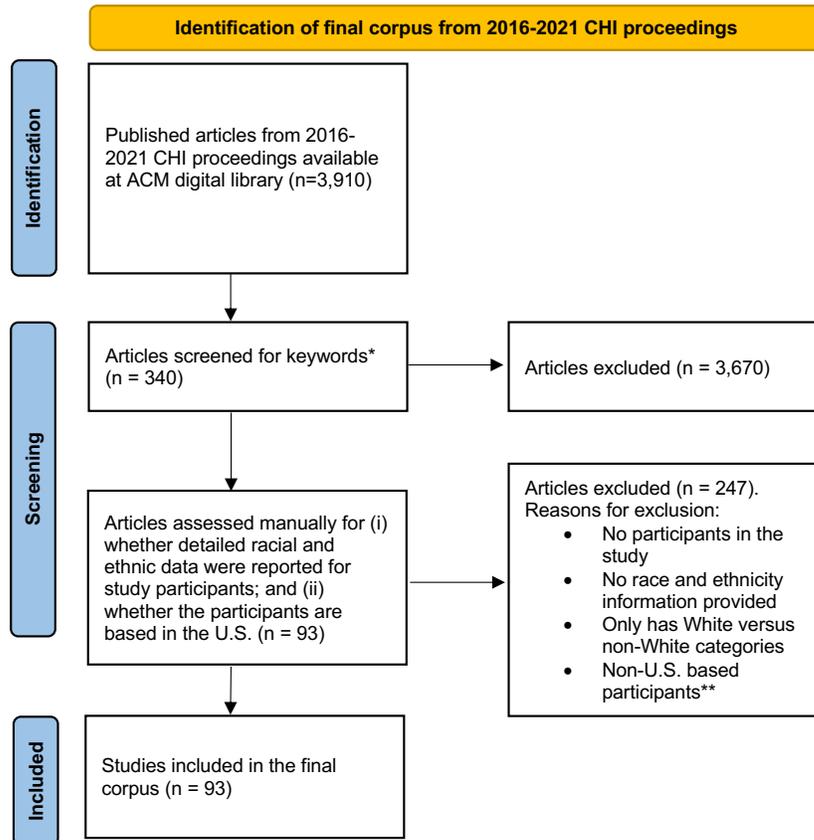
Figure 3: The flow of information through different phases of the corpus curation process as described in Section 3.1. We displayed the inclusion and exclusion criteria, as well as the final number resulting publications of each stage.