Title
An Automated Algorithm for Classifying Expansive Responses for Gender Identity

Authors
Ceja, Alexis
Raygani, Sawye
Conner, Bradley T
et al.

Publication Date
2023-11-07

An Automated Algorithm for Classifying Expansive Responses for Gender Identity

Alexis Ceja, BA[1,2], Sawye Raygani, BS[3], Bradley T. Conner, PhD[4], Nadra E. Lisha, PhD[2,5], Kinsey B. Bryant-Lees, PhD[2,6], Micah E. Lubensky, PhD[1,2], Mitchell R. Lunn, MD, MAS[2,7,8], Juno Obedin-Maliver, MD, MPH, MAS[2,8,9], & Annesa Flentje, PhD[1,2,10]

[1]Department of Community Health Systems, School of Nursing, University of California, San Francisco, San Francisco, CA, USA
[2]The PRIDE Study/PRIDEnet, Stanford University School of Medicine, Stanford, CA, USA
[3]School of Medicine, University of California, San Diego, La Jolla, CA, USA
[4]Department of Psychology, Colorado State University, Fort Collins, CO, USA
[5]Center for Tobacco Control, Research, and Education, Division of General Internal Medicine, Department of Medicine, University of California San Francisco, San Francisco, CA, USA
[6]Department of Psychological Sciences, Northern Kentucky University, Highland Heights, KY, USA
[7]Division of Nephrology, Department of Medicine, Stanford University School of Medicine, Stanford, CA, USA
[8]Department of Epidemiology and Population Health, Stanford University School of Medicine, Stanford, CA, USA
[9]Department of Obstetrics and Gynecology, Stanford University School of Medicine, Stanford, CA, USA
[10]Alliance Health Project, Department of Psychiatry and Behavioral Sciences, School of Medicine, University of California San Francisco, San Francisco, CA, USA

Corresponding author: Annesa Flentje, 2 Koret Way, San Francisco, CA 94143, annesa.flentje@ucsf.edu

Disclosures: The authors declare the following relationships which may be considered potential conflicts of interest. Dr. Juno Obedin-Maliver has consulted for Sage Therapeutics (2017), Ibis Reproductive Health (2017-2018, 2020-present), Hims, Incorporated (2019-present), and Folx, Incorporated (2019-present). None of these engagements influenced or are pertinent to the work described in this manuscript. Dr. Mitchell R. Lunn has received consulting fees from Folx Health (2019 – 2021), Hims, Inc. (2019 – present), Otsuka Pharmaceutical Development and Commercialization, Inc. (2023), and American Dental Association (2024). The remaining authors have no conflicts of interest to disclose.

Funding: This project was funded by the National Institute on Drug Abuse and the Office of Research on Women's Health (R01DA052016 to Dr. Flentje). It was also supported by the National Institute on Drug Abuse (K23DA0398001 to Dr. Flentje), the National Institute of Diabetes and Digestive and Kidney Diseases (K12DK11028 to Dr. Obedin-Maliver), and the Patient-Centered Outcomes Research Institute® (PCORI®) (PPRN-1501-26848 to Dr. Lunn). The funding institutions did not contribute to the study design, collection and analysis of data, and writing of the manuscript.

Abstract

Current two-step measures of gender identity do not prescribe methods for using expanded responses (*e.g.,* multiple selections) among sexual and gender minority (SGM) people, though they want the opportunity to provide these responses. To increase statistical power using expanded gender identity responses, we created an automated algorithm to generate analyzable categories. Participants' expanded gender identity responses and sex assigned at birth were used to create five categories (i.e., cisgender men, cisgender women, gender expansive individuals, transgender men, and transgender women) from a cohort of SGM people (N = 6,312, 53% cisgender individuals). Data was collected from June 2020 to June 2021. Chi-square tests were performed to assess the association between the algorithm-generated and participant-selected gender categories, and to identify demographic differences between participants in the algorithm-generated categories. Forty-six percent of our sample may have been classified into an "other" category without an algorithm due to writing their own response (5.7%), selecting "another gender identity" (5.7%), or selecting multiple (42.6%) or less commonly described (10.2%) gender identities. There was a relationship between the categories formed by our algorithm and participants' single category selection ($\chi2$ [20] = 19,000, $p < .001$). Concordance rates were high (97-99%) among all groups except for participants classified as gender expansive (74.3%). Without an algorithm to incorporate expanded gender identity responses, almost half of the sample may have been classified into an "other" category or dropped from analyses. Our algorithm successfully classified participants into analyzable categories from expanded gender responses.

Public Significance Statement: The present study demonstrates the effectiveness of an automated algorithm in classifying LGBTQIA+ people – including participants who identify as transgender and non-binary – into concise, analyzable gender categories using open-ended and multiple selection responses.

This study identified methods for using expanded responses for gender identity as a tool to identify and ameliorate health disparities among LGBTQIA+ people, particularly transgender people.

Introduction

According to U.S. population health surveys, an estimated 1.2 million people aged 18 to 60 years identify as gender minority (GM, *i.e.,* individuals whose gender identity differs from that often associated with their sex assigned at birth [SAAB], Wilson & Meyer, 2021). Approximately 76% of GM adults are under the age of 30 years, illustrating the rise in GM identification among younger generations (Wilson & Meyer, 2021). The historical mistreatment and stigmatization of GM people in research has contributed to greater hesitancy to participate in research due to fear of discrimination (Kattari et al., 2021). When GM people engage in research, they are often inundated with gender identity measures that fail to accurately account for their diverse lived experiences and identities (Reisner et al., 2015), despite extensive health research demonstrating the importance of accounting for GM status (Lefevor et al., 2019; Newcomb et al., 2019).

To prevent the conflation of gender identity and sex and to ensure accurate classification of GM people, a growing number of researchers and organizations, like the National Academies of Sciences, Engineering, and Medicine (*Measuring Sex, Gender Identity, and Sexual Orientation*, 2022), have advocated for the use of a two-step approach in which participants are asked about their gender identity and SAAB separately (Lombardi & Banik, 2016; Reisner, Biello, et al., 2014; Reisner, Conron, et al., 2014; Tate et al., 2013; The Gender Identity in U.S. Surveillance (GenIUSS) Group, 2014; Young & Bond, 2023). A recent study conducted in a sexual health clinic found that utilization of the two-step approach from a one-step question increased identification of GM participants by 4.8-fold, thereby reducing misclassification (Tordoff et al., 2019). Additionally, prior work has demonstrated high acceptability of the two-step approach among community samples diverse in race, ethnicity, and gender (Cahill et al., 2014; Lombardi & Banik, 2016; Reisner, Biello, et al., 2014). Measures for gender identity using the two-step approach may be limited by the use of forced-choice questions, single-select options, and exclusion of open-ended answer choices, resulting in misclassification, and in some instances, the misgendering of GM people. This may reduce participant engagement (Tate et al., 2013), compromise the study's validity (Bauer et al., 2017), and hinder the identification and elimination of health disparities among this population (Patterson et al., 2017). While predefined, limited gender identity options can benefit researchers in maintaining sufficient sample size for analytic utility, these response options may introduce feelings of discomfort and alienation among GM people (Scheffey et al., 2019). This highlights the significance of utilizing inclusive measures for gender identity informed by the preferences of GM people.

Prior work has demonstrated that sexual and gender minority (SGM) participants want the opportunity to select multiple answer choices and provide a written description of their gender identity (Beischel et al., 2022; Suen et al., 2020; Vivienne et al., 2021). Moreover, GM people have specified additional recommendations for measures of gender identity such as the inclusion of frequently endorsed identities within GM populations (*e.g.,* non-binary and agender, Puckett et al., 2020). Changes in self-reported gender identity over time and endorsement of more than one gender identity term is common among GM people, potentially attributed to evolving language and understanding of gender identity (Ocasio et al., 2024). However, using expanded options for gender identity can make analysis of group differences difficult, and there remains little guidance on how to create analyzable categories that are inclusive of participants' diverse gender identities. Some scholars have created an "other" category consisting of participants who selected multiple or less commonly described gender identities, provided their own write-in response, or selected "another gender identity." However, these data may be removed entirely from analyses because of the heterogeneity of these identities (Ridolfo et al., 2012). In a sample of 794 open-ended gender identity responses, nearly 99% of participants were categorized into predefined gender identity categories, suggesting the feasible yet time-consuming nature of classifying open-ended responses without computerized methods (Lindqvist et al., 2021). Without a systematic method of classification, researchers are challenged with manually classifying open-ended responses, which can be particularly difficult in large population-based studies (Reisner et al., 2015; Young & Bond, 2023). To encourage utility of expanded response options for gender identity, researchers must have efficient methods to accurately and systematically capture the diverse identities and experiences within the SGM population.

Implementation of an automated algorithm compared to manual coding can optimize the classification of gender identity, thereby reducing the time and effort required by researchers to classify expanded responses for gender identity. A noteworthy disadvantage arises from the potential introduction of researcher bias in the development and refinement of the algorithm, given that the research team determines which responses constitute each respective gender identity category. Despite potential disadvantages, significant benefits may emerge from the use of an automated algorithm such as increased transparency about the methodologies employed and replicability across datasets. Emerging computerized methods have been designed to create gender identity categories from expanded options (*e.g.,* the "gendercoder" package in R (Beaudry et al., n.d.) and a hierarchical clustering algorithm (Callander et al., 2021)). However, these methods have not examined the concordance of these computer-generated categories with the category that participants would choose when presented with reduced, single-select options; it is unknown if these algorithms place participants into the gender category that they believe best describes them.

Objective

The purpose of this study was to establish an automated algorithm to create analyzable categories (*i.e.,* cisgender men, cisgender women, gender expansive individuals, transgender men, and transgender women) from participants' multiple selections and open-ended responses for gender identity, extending prior work (Flentje et al., 2020). We aimed to determine the percentage of participants who may have been classified into an "other" category or removed from analyses without a similar method. We also sought to identify the concordance of the gender identity categories established by our algorithm with the single category that participants chose from reduced, predefined answer choices (*i.e.,* "cisgender man," "cisgender woman," "non-binary," "transgender man," "transgender woman," and "another gender identity"). Lastly, we sought to identify if there were demographic differences (*i.e.,* age, education, geographic region, income, race and ethnicity, and sexual orientation) in the performance of our algorithm between participants who were classified into a gender identity category that was concordant *versus* discordant with their single category response. We hypothesized that there would be demographic differences between these two groups due to the dynamic nature of demographic characteristics in shaping individuals' lived experiences.

Materials and Methods

Participants

Participants were enrolled in The PRIDE Study, a national, longitudinal cohort of SGM people. To be eligible for The PRIDE Study, participants must identify as lesbian, gay, bisexual, transgender, queer, or another sexual and/or gender minority, be 18 years or older, live in the United States or its territories, and be comfortable reading and understanding English. Participants are recruited through PRIDEnet Community Partners consisting of SGM health centers and organizations, in-person events, advertisement on social media, and by word-of-mouth (Lunn et al., 2019). Participants were included in the current study if they provided information about their gender identity in The PRIDE Study's 2020 Annual Questionnaire. A detailed description of the bot protection measures utilized can be found in Supplementary Material 1. Data collection was from June 2020 to June 2021. The PRIDE Study was approved by the institutional review boards of the University of California, San Francisco, Stanford University, and the WIRB-Copernicus Group (WCG). WCG IRB approved a request for a waiver of consent signature and a partial waiver of authorization for use and disclosure of protected health information (PHI).

Measures

We assessed gender identity using two methods as shown in Figure 1. The first method permitted multiple selections for gender identity as well as an option to provide a written description of one's gender identity. Participants were asked, "What is your current gender identity?" with 12 choices: "agender," "cisgender man," "cisgender woman," "genderqueer," "man," "non-binary," "questioning," "transgender man," "transgender woman," "Two-spirit," "woman," and "another gender identity." Participants who selected "another gender identity" could provide a description of their gender identity. The first method appeared at the beginning of the 2020 Annual Questionnaire with other demographic variables (*i.e.,* SAAB, intersex status, and sexual orientation). This section was followed by the second method that involved self-classification into a single category from reduced, predefined answer choices: "If you had to choose only one of the following terms, which best describes your current gender identity?" with 6 choices (*i.e.,* "cisgender man," "cisgender woman," "non-binary," "transgender man," "transgender woman," and "another gender identity"). In the second method, the term "cisgender" was defined and an example was provided. With this method, participants who selected "another gender identity" could not provide a written description of their gender identity. SAAB was assessed by asking participants: "What was the sex assigned to you at birth, for example, on your original birth certificate?" with answer choices of "female" and "male."

Additional demographics included age, education, geographic region, income, race and ethnicity, and sexual orientation. Education level was measured by asking participants their highest education level with 10 answer choices offered (*i.e.,* "no schooling;" "nursery school to high school, no diploma;" "high school graduate or equivalent (*e.g.,* GED);" "trade/technical/vocational training;" "some college;" "2-year college degree;" "4-year college degree;" "Master's degree;" "Doctoral degree;" and "Professional degree (*e.g.,* M.D., J.D., M.B.A.)." Geographic region was determined from participants' self-reported ZIP codes and was categorized into 4 U.S. Census Regions: Midwest, Northeast, South, and West. To assess income level, participants were asked to report their individual earnings (in US Dollars) before taxes and deductions from all sources in the 2019 tax year. Eighteen answer choices in increments of $9,999 (ranging from $0 to $200,001+) were provided. Race and ethnicity were assessed by the single item: "Which categories best describe you?" with 8 options: "American Indian or Alaska Native;" "Asian;" "Black, African American or African;" "Hispanic, Latino or Spanish;" "Middle Eastern or North African;" "Native Hawaiian or other Pacific Islander;" "White;" and "none of these fully describe me."

Participants who selected “none of these fully describe me” could provide a written description of their race and/or ethnicity. Sexual orientation was assessed by the item, “What is your current sexual orientation?” with 11 options (*i.e.,* “asexual,” “bisexual,” “gay,” “lesbian,” “pansexual,” “queer,” “questioning,” “same-gender loving,” “straight/heterosexual,” “Two-spirit,” and “another sexual orientation” with an accompanying open-ended response). Multiple answer choices were permitted for race and ethnicity and for sexual orientation.

Automated algorithm

We developed an automated algorithm in which we classified participants into 5 mutually exclusive categories (*i.e.,* cisgender men, cisgender women, gender expansive individuals, transgender men, and transgender women) based on expanded responses for gender identity and SAAB. We defined cisgender men as participants who reported one or more gender identities exclusively within the masculine binary (*e.g.,* “man” and “cisgender man”) and were assigned male sex at birth. No participants classified through our algorithm as cisgender men provided a written description of their gender identity. We defined cisgender women as participants who reported one or more gender identities exclusively within the feminine binary (*e.g.,* “woman” and “cisgender woman”) and were assigned female sex at birth. Examples of open-ended responses included “femme” and “lesbian.” We defined gender expansive individuals as participants who reported one or more gender identities beyond the binary (*e.g.,* “agender,” “genderqueer,” “non-binary,” “questioning,” and “Two-spirit”). Examples of open-ended responses included “bigender,” “genderfluid,” and “neutrois.” Participants who selected one or more gender identities beyond the binary, regardless of whether they selected additional options such as those corresponding to a cisgender or transgender identity, were classified as gender expansive, aligning with existing definitions of the term (*e.g.,* National Institutes of Health, 2024). We defined transgender women as participants who reported one or more gender identities exclusively within the feminine binary (*e.g.,* “transgender woman” and “woman”) and were assigned male sex at birth. Examples of open-ended responses were “transsexual woman” and “trans feminine.” We defined transgender men as participants who reported one or more gender identities exclusively within the masculine binary (*e.g.,* “transgender man” and “man”) and were assigned female sex at birth. Examples of open-ended responses included “man of trans experience” and “transmasculine.” We recognize the divergence in definitions of “transmasculine” and “transfeminine” within research and society. We chose to define these terms more closely to a transgender than a non-binary identity for consistency with prior work within The PRIDE Study (Flentje et al., 2020). This decision was substantiated in the current study, with 80% (n = 48) of the subsample of 60 participants who wrote in a response of “transmasculine” or “transfeminine” choosing a single category selection that aligned with the algorithm-generated category. We did not omit responses that might be considered implausible, for example, participants who selected “cisgender man” and reported an assignment of female at birth were included in the sample. This decision was made to be consistent with the community engaged philosophy of our study (Obedin-Maliver et al., 2024), and to respect the diverse lived experiences and identities within the sample.

Our algorithm used open-ended responses to identify strings associated with five terms related to gender identity – cisgender, feminine, masculine, non-binary, and transgender – and incorporated the coding of these strings into the final category determination. Examples of strings associated with these terms are available through Figure 2. We utilized open-ended responses to identify strings associated with intersex status (*e.g.,* “intersex”); however, this coding only determined the final category assigned for select cases. For instance, participants who wrote an intersex-related identity and selected no other gender identity responses were classified as gender expansive individuals. Our algorithm was developed and refined using data from The PRIDE Study’s 2017-2020 Annual Questionnaires. Our algorithm is provided in Supplementary Materials 2 (PDF version of the code), 3 (Stata version of the code) and 4 (R version of the code). Examples of gender identity classification using actual participant responses is presented in Table 1.

Analysis

Data analysis was completed using Stata software, Version 17 (StataCorp, 2021) and R software, Version 4.2.3 (R Core Team, 2023). We tabulated the frequency of participants who may have been classified into an "other" category or dropped from analyses without an algorithm due to selecting "another gender identity," providing their own write-in response, or selecting multiple or less commonly described gender identities (*e.g.,* agender). Two chi-square (χ^2) tests of independence were performed to (1) investigate the relationship between the two methods of assessing gender identity (*i.e.,* using our algorithm and the single category participants chose from reduced, predefined answer choices and (2) examine whether there were bivariate demographic differences (*i.e.,* age, education, geographic region, income, race and ethnicity, and sexual orientation) between the gender identity categories participants were assigned to using our algorithm. For analysis of differences by age, we created four categories: (1) 18-30, (2) 31-45, (3) 46-60, and (4) 61 and older (Mehta et al., 2020). Since the categories for the race and ethnicity, and sexual orientation measures were not mutually exclusive, we created dichotomous variables for each category and assessed each in separate tests.

To examine demographic differences (*i.e.,* age, education, geographic region, income, race and ethnicity, and sexual orientation) between participants who were classified into a gender identity category by our algorithm corresponding with their single category selection (classification concordance) and those who were placed in a category that did not correspond with their single category selection (classification discordance), we conducted a multivariable logistic regression. In the analysis, each demographic characteristic was treated as an independent variable, and discordance was treated as the outcome variable. Concordance for the gender expansive category was met when participants selected "non-binary" or "another gender identity" as their single category response. To prevent bias, we used complete case analysis to handle the missing data. Consistent with the chi-square analyses, each race and ethnicity, and sexual orientation term was dichotomized to participants who endorsed the term and those who did not; the reference group for each term was participants who did not report the term. For age, education, and income, the lowest category for each was used as the reference group, representing the baseline for each demographic characteristic (*e.g.,* the reference group for age was participants aged 18 to 30 years). Region was treated as an indicator variable. The reference group for region was participants who reported residency in the West, as this was the largest group.

Data availability

Due to ethical restrictions related to sensitive participant information, study data can be made available on request in accordance with certain data access conditions by contacting research@pridestudy.org.

Code availability

The algorithm to classify expanded responses for gender identity is available within the supplementary materials.

Results

Of the 6,312 participants in the sample, 23.3% (*n* = 1,473) were classified as cisgender men, 30.1% (*n* = 1,898) as cisgender women, 33% (*n* = 2,086) as gender expansive individuals, 9.3% (*n* = 586) as transgender men, and 4.3% (*n* = 269) as transgender women. The majority of the sample identified as White only (81.4%), had a college, graduate, or professional degree (76.4%), and lived in the Western or Southern regions of the U.S. (59.2%). Participants classified as gender expansive and transgender men had lower median ages (27.2 and 27.5, respectively) than those classified as cisgender men (42.9), cisgender women (30.9), and transgender women (41.6). Participants classified as cisgender men, and transgender women often reported an income above $40,000, whereas participants classified as cisgender women, gender expansive and transgender men typically reported an income below $40,000. The most frequently reported sexual orientation among participants classified as cisgender men was gay. The sexual orientations of lesbian and queer were often endorsed by participants classified as cisgender women. Participants who were classified as gender expansive typically identified as queer, participants who were classified as transgender men commonly identified as bisexual and queer, and participants who were classified as transgender women frequently identified as lesbian. Approximately 1.3% (*n* = 81) of our sample did not select a category from the reduced, predefined answer choice list, yet provided information about their gender identity when given expanded options. Among these participants, 19.8% (n = 16) were classified by our algorithm as cisgender men, 33.3% (n =27) as cisgender women, 27.2% (n = 22) as gender expansive, 16% (n = 13) as transgender men, and 3.7% (n = 3) as transgender women.

Demographic differences between individuals in categories created through our algorithm

Differences in demographics by the algorithm-generated gender identity categories are presented in Table 2. The individuals in categories formed through our algorithm significantly differed by age (χ^2 [12] = 1,000, p < .001), education (χ^2 [12] = 299.6, p < .001), geographic region (χ^2 [12] = 83.6, p < .001), income (χ^2 [12] = 597.2, p < .001), and sexual orientation (χ^2 [4] = 22.9-2,900, p < .001 for all). In addition, there were differences by specific racial and ethnic categories including American Indian or Alaska Native (χ^2 [4] = 13.3, p = .010); Middle Eastern or North African (χ^2 [4] = 13.8, p = .008); White (χ^2 [4] = 15.9, p = .003); participants who reported that "none of the [racial and ethnic] categories fully described [them]" (χ^2 [4] = 20.1, p < .001), and participants who selected more than one race and/or ethnicity (χ^2 [4] = 42.3, p < .001).

Participants who may have been classified into an "other" category or removed from analyses

Almost half of our sample (44.6%, n = 2,813) may have been classified into an "other" category or dropped from analyses without an algorithm including participants who selected "another gender identity" (5.7%, n = 362), provided their own write-in response (5.7%, n = 359), or reported multiple (42.6%, n = 2,687) or less commonly described (*i.e.,* agender, questioning, and Two-spirit, 10.2%, n = 646) gender identities.

Two methods for assessing gender identity

The gender identity categories created through our algorithm and the single category participants chose from reduced, predefined answer choices were significantly related (χ^2 [20] = 19,000, p < .001). The observed frequencies are reported in Table 2. Visual inspection of the χ^2 table suggests that our algorithm successfully assigned the same category that participants chose for their single category selection under the reduced choice model in at least 97% of the cases except for gender expansive individuals (74.3% match): cisgender man (98.8% match), cisgender women (99.0% match), transgender men (98.1% match), and transgender women (97.0% match).

We identified several common response patterns among participants who were classified into a gender identity category by our algorithm that was discordant with their single category selection under the reduced choice model. Among the participants classified as cisgender men through our algorithm who self-selected a category other than “cisgender man” (n = 17), 82.4% identified as a “man” under the expanded choice model and chose “another gender identity” (n =12) or “non-binary” (n = 2) as their single category response under the reduced choice model. A similar pattern emerged among participants who were classified as cisgender women through our algorithm but self-selected a category other than “cisgender woman” (n = 19); most (94.7%) identified as a “woman” under the expanded choice model and chose “another gender identity” (n =14) or “non-binary” (n = 4) as their single category selection under the reduced choice model. Participants who were classified by our algorithm as gender expansive and selected a category other than “another gender identity” or “non-binary” under the reduced choice model (n = 530) typically identified with one or more gender identities beyond the binary (*e.g.,* “cisgender woman” and “non-binary”) under the expanded choice model. Among these participants, 12.8% (n = 68) self-selected “cisgender man,” 40.6% (n = 215) “cisgender woman,” 35.9% (n = 190) “transgender men,” and 10.8% (n = 57) “transgender women” as their single category response under the reduced choice model. The majority of these participants identified with one or more gender expansive term (*i.e.,* “agender,” “genderqueer,” “non-binary,” “questioning,” and “Two-spirit”) (n = 507); this may have been in addition to other gender identity answer choices. Of the participants categorized as transgender men through our algorithm who chose a category other than “transgender man” (n = 11), most identified with binary terms that did not include the word *cisgender* (*i.e.,* “transgender man” and “man”) under the expanded choice model and chose “another gender identity” (n = 4), “cisgender man” (n = 4), or “non-binary” (n = 2) as their single category response. Similarly, participants categorized as transgender women through our algorithm who chose a category other than “transgender woman” ($n = 8$) typically identified as a “woman” and/or “transgender woman” under the expanded choice model and selected “another gender identity” ($n = 4$), “cisgender woman” ($n = 3$), or “non-binary” ($n = 1$) as their single category response.

A small proportion of the sample (< 1%; $n = 60$) selected “another gender identity” and wrote in a response of “transmasculine” or “transfeminine.” The majority of these participants (80%, $n = 48$) were classified into concordant algorithm-generated and self-selected gender categories. Among the 12 participants who wrote in a response of “transmasculine” or “transfeminine” and were classified into discordant gender categories, 83.3% ($n = 10$) chose “transgender man” or “transgender woman” under the reduced choice model and were classified by the algorithm as gender expansive. All ten of these participants selected a gender expansive term (*e.g.*, non-binary) in addition to “another gender identity,” aligning with our definition of gender expansive individuals. One participant selected “another gender identity” as their single selection and was classified as a transgender man. The participant was assigned to the transgender men category by the algorithm because they reported “another gender identity,” describing their gender as “transmasculine” in the open-ended response. The remaining participant chose cisgender woman under the reduced choice model and was classified as gender expansive. The participant reported multiple genders within and beyond the binary (*e.g.*, cisgender woman and gender nonconforming), and was subsequently classified into the gender expansive category due to their endorsement of gender expansive terms.

Demographic differences between participants in concordant *versus* discordant categories

Demographic information of participants who were classified in a gender identity category concordant *versus* discordant with the single category they selected from reduced, predefined answer choices is presented in Table 3. Participants who reported an identity of Native Hawaiian or other Pacific Islander were removed from this particular analysis ($n = 14$) due to the absence of variability in concordance/discordance among this group; all participants who reported this identity were in concordant categories. Higher income (OR = .88, *p* = .009) and education (OR = .85, *p* = .019) were associated with a lower likelihood of being classified into discordant self-selected and algorithm-generated categories. Residence in the Midwestern and Northeastern geographic regions of the U.S. (OR = 1.27-1.38, *p* = .016-.074) was associated with a greater likelihood of being in discordant categories compared to those living in the West. Additionally, participants who identified as Middle Eastern or North African (OR = 2.26, *p* = .033), selected that "none of the [racial and ethnic] categories fully described [them]" (OR = 2.41, *p* = .019), or identified as pansexual (OR = 1.35, *p* = .026), queer (OR = 1.57, *p* = .002), or same-gender loving (OR = 1.67, *p* = .005) were more likely to be in discordant gender identity categories.

Discussion

Despite a growing body of research illustrating the desire from SGM communities for expanded gender identity choices (Beischel et al., 2022; Suen et al., 2020; Vivienne et al., 2021), this is the first study, to our knowledge, that has established an automated algorithm to create analyzable categories to account for these expanded choices among a large, diverse sample of SGM participants and compared these categories with participants' single reduced category selection. The gender identity categories established through our algorithm differed significantly by age category, education, geographic region, income, all sexual orientation terms, and specific racial and ethnic categories including American Indian or Alaska Native; Middle Eastern or North African; White; participants who reported that "none of the [racial and ethnic] categories fully described [them]," and participants who selected more than one race and/or ethnicity. These findings challenge the idea that gender identity can be treated as a covariate in analyses because it is not equally distributed across demographic characteristics. Methods will be needed to identify how to incorporate gender identity into future studies without assuming an equal distribution of gender identity.

Consistent with prior work (Kuper et al., 2012; Lunn et al., 2019), a large proportion (44.6%) of our sample selected multiple or less common gender identities, provided their own write-in response, or selected "another gender identity," underscoring the importance of including expanded choices in measures of gender identity. These participants may have been grouped into an "other" category or dropped from analyses completely. Our findings indicated that the gender identity categories created through our algorithm were highly related to participants' single category selection. Accurate classification of gender identity into more concise categories is important to increase the statistical power of the analyses for group comparison. By having sufficient statistical power, analyses can improve knowledge about and identification of SGM subgroups at greater risk for specific health outcomes and contribute to effective resource allocation.

When examining the relationship between the two methods of assessing gender identity (*i.e.,* our algorithm and the single category participants chose from reduced, predefined answer choices), our algorithm exhibited a weaker association with the participant-selected category for those classified into the algorithm-generated gender expansive category. Approximately a quarter (25.7%) of participants who were classified as gender expansive individuals by our algorithm did not select "non-binary" or "another gender identity" as their single category selection. These participants selected terms beyond the binary (*e.g.,* non-binary) when offered expanded options, but most chose a binary gender (*e.g.,* cisgender woman) for their single category selection. The benefit of using an algorithm, where researchers determine gender classification based on expanded answer choices for gender identity, as opposed to participants choosing their own gender category is that individuals with similar responses for gender identity and SAAB are grouped together as they may share similar lived experiences. When participants self-select their gender category from reduced options, plausible differences in the understanding and usage of certain terms (*e.g.,* cisgender) may be observed. Nevertheless, this option provides participants with more autonomy and decision-making power in how they are grouped within research. Our algorithm may reveal underlying differences in gender identity that are not captured when participants are required to select one category from a reduced, predefined answer choice list. Alternatively, participants' selection of a single gender identity category that best describes them may be a better metric of related health outcomes than a category chosen by researchers. Future studies are needed to understand if participants who were classified as gender expansive through our algorithm whose classification was discordant with their single category selection have health outcomes more similar to those classified into the algorithm-generated gender expansive category who selected "another gender identity" or "non-binary" for their single category selection, or to those classified into an algorithm-generated binary category (*e.g.,* cisgender women).

The algorithm worked well for participants in the remaining four gender identity categories: cisgender men, cisgender women, transgender men, and transgender women (concordance rates ranged from 97-99%). Nearly all participants who were classified by our algorithm as cisgender men or women self-selected "cisgender man" or "cisgender woman" for their single category selection, yet a small percentage self-selected "another gender identity." This may be due to a dislike of the term "cisgender" as utilized in "cisgender men" and "cisgender women," which were two options from the reduced, predefined answer choice list. Although we define the term "cisgender" in our annual questionnaires, we have received direct feedback from some older cisgender participants who are sexual minority (*e.g.,* cisgender lesbian women) about their dislike for the term because it does not reflect their lived experiences. This dislike may be attributed to generational differences in the language and conceptualization of gender identity and lack of transgender-inclusive measures in research with older sexual minority adults (Institute of Medicine, 2011).

Higher income and education were associated with lower odds of being in discordant self-selected and algorithm-generated categories. This may be attributed to greater opportunities for identity exploration and development through increased access to supportive, identity-affirming communities. Conversely, participants with a greater likelihood of being classified into a gender category discordant with their single category selection may have less access to identity-affirming communities. These participants included those who lived in the Midwest or Northeast, reported an identity of "Middle Eastern or North African," chose that "none of the [racial and ethnic] categories fully described [them], or identified as pansexual, queer, or same-gender loving. Future work is needed to explore potential reasons for the observed demographic differences between participants in concordant *versus* discordant gender categories. Replication of our algorithm in other data sets could provide insight into whether these findings are unique to the current study or evident across datasets.

Limitations

There were several important limitations to this work. Despite our large sample, we had comparatively smaller samples of transgender men (9.3%) and transgender women (4.3%). The sample was predominantly White only (81.4%), though we did have large enough samples of racial or ethnic minority SGM people to enable comparisons by race and ethnicity. Implementation of the algorithm in samples with greater representation from transgender men and women, in samples with greater racial and ethnic diversity, and in non-SGM samples is imperative to ensure that our algorithm can capture the identities and experiences of these subpopulations and to identify new language and terminology used to describe gender identity. The replicability of our algorithm in other datasets is dependent upon the answer choices provided in the gender identity measure used. Studies using measures with reduced answer choices may have more diverse open-ended responses than those with a broader range of choices, which may require more time to modify the algorithm to recognize and correctly classify participants based on these additional responses. We acknowledge that responses that may be considered inconsistent (*e.g.,* endorsement of both "cisgender man" and "woman") may be attributed to participant error, potentially introducing concerns about data quality. These responses were included in the analyses to respect participant autonomy and the diversity of identities within the sample. We actively sought to approach our methodology in a way that would be affirming to transgender and gender expansive individuals. Future replications of the current study should explore methodologies for identifying and addressing participant error.

Conclusion

Researchers are encouraged to assess gender identity using a two-step approach and provide participants with the option of selecting multiple responses and including their own write-in response.

The obtained data can be difficult to analyze, however, through the implementation of our algorithm, we were able to successfully classify participants into concise gender identity categories; these classifications were highly concordant with their single category selection. This suggests that the algorithm may be used and adapted for other data sets to create analyzable categories from expanded answer choices for gender identity. Demographic differences were found between participants in the gender identity categories created by our algorithm and between participants who were classified into a category concordant *versus* discordant with their single category response. Without our algorithm, nearly half of our sample may have been placed into an "other" category or removed from analyses. Rigorous methodology must be applied in research and clinical practice to ensure appropriate classification of gender identity for SGM people who have diverse identities and lived experiences.

Table 1

Example gender identity classification using actual participant responses

Gender Identity Category	Selection(s) using the Expanded Choice Model	Open-Ended Gender Identity Response	Participant-Reported Sex Assigned at Birth	Algorithm Number
Cisgender men	"Cisgender man"	None	"Male"	6
Cisgender woman	"Cisgender woman"	None	"Female"	1
	"Another gender identity" and "Cisgender woman" and "Woman"	"Femme"	"Female"	3
Gender expansive	"Agender" and "Non-binary"	None	"Female"	19
	"Cisgender man" and "Woman"	None	"Female"	20
Transgender men	"Transgender man"	None	"Female"	11
	"Another gender identity" and "Man" and "Transgender man"	"Transmasculine"	"Female"	12
Transgender women	"Transgender woman"	None	"Male"	15
	"Another gender identity" and "Transgender woman," and "Woman"	"Lesbian"	None	17

Note. Please see Supplemental Materials 2, 3, or 4 for all algorithms.

Table 2

Demographics of participants who reported gender identity information by the category assigned through our algorithm in The PRIDE Study's 2020 Annual Questionnaire (N = 6,312)

Variable	Cisgender men (N = 1,473)	Cisgender women (N = 1,898)	Gender expansive individuals (N = 2,086)	Transgender men (N = 586)	Transgender women (N = 269)	p
Expanded gender identity answer choices[a] (n, %)						
Agender	0 (0)	0 (0)	318 (15.2)	0 (0)	0 (0)	
Cisgender man	905 (61.4)	0 (0)	47 (2.3)	3 (.5)	0 (0)	
Cisgender woman	0 (0)	1,487 (78.3)	138 (6.6)	0 (0)	2 (.7)	
Genderqueer	0 (0)	0 (0)	845 (40.5)	0 (0)	0 (0)	
Man	874 (59.3)	0 (0)	166 (8)	290 (49.5)	0 (0)	
Non-binary	0 (0)	0 (0)	1,465 (70.2)	0 (0)	0 (0)	
Questioning	0 (0)	0 (0)	295 (14.1)	0 (0)	0 (0)	
Transgender man	0 (0)	0 (0)	291 (14)	553 (94.3)	0 (0)	
Transgender woman	0 (0)	0 (0)	90 (4.3)	0 (0)	255 (94.8)	
Two-spirit	0 (0)	0 (0)	54 (2.6)	0 (0)	0 (0)	
Woman	0 (0)	891 (46.9)	378 (18.1)	0 (0)	126 (46.8)	
Another gender identity	0 (0)	14 (.7)	332 (15.9)	14 (2.4)	2 (.7)	
Selected more than one gender identity	306 (20.8)	490 (25.8)	1,507 (72.2)	269 (45.9)	115 (42.8)	
Reduced, single-select gender identity answer choices (n, %)						
Cisgender man	1,440 (98.8)	1 (.1)	68 (3.3)	4 (.7)	0 (0)	
Cisgender woman	1 (.1)	1,852 (99)	215 (10.4)	0 (0)	3 (1.1)	
Non-binary	2 (.1)	4 (.2)	1,362 (66)	2 (.4)	1 (.4)	
Transgender man	1 (.1)	0 (0)	190 (9.2)	562 (98.1)	0 (0)	
Transgender woman	1 (.1)	0 (0)	57 (2.8)	1 (.2)	258 (97)	
Another gender identity	12 (.8)	14 (.7)	172 (8.3)	4 (.7)	4 (1.5)	
Sex assigned at birth (n, %)						
Female	0 (0)	1,898 (100)	1,795 (86.3)	583 (99.7)	1 (.4)	

Male	1,473 (100)	0 (0)	286 (13.8)	2 (.3)	267 (99.6)	
Age, in years, median (IQR)	42.9 (30.9-57.5)	30.9 (25.3-40.3)	27.2 (23-33.7)	27.5 (21.8-35.8)	41.6 (30.5-56.8)	**< .001**
Race and ethnicity[a] (*n, %*)						
American Indian or Alaska Native	32 (2.2)	53 (2.8)	86 (4.1)	24 (4.1)	10 (3.7)	**.010**
Asian	71 (4.8)	89 (4.7)	131 (6.3)	27 (4.6)	12 (4.5)	.134
Black, African American, or African	57 (3.9)	73 (3.9)	93 (4.4)	27 (4.6)	8 (3.0)	.654
Hispanic, Latino, or Spanish	121 (8.2)	127 (6.7)	141 (6.8)	47 (8)	17 (6.3)	.340
Middle Eastern or North African	13 (.9)	22 (1.2)	45 (2.2)	5 (.9)	3 (1.1)	**.008**
Native Hawaiian or other Pacific Islander	1 (.1)	5 (.3)	5 (.2)	2 (.3)	1 (.4)	.661
White	1,288 (87.4)	1,733 (91.3)	1,880 (90.1)	530 (90.4)	248 (92.2)	**.003**
None of these fully describe me	12 (.8)	25 (1.3)	49 (2.3)	3 (.5)	6 (2.2)	**< .001**
Selected more than one race and/or ethnicity	111 (7.5)	205 (10.8)	300 (14.4)	76 (13)	29 (10.8)	**< .001**
Sexual orientation[a] (*n, %*)						
Asexual	19 (1.3)	153 (8.1)	412 (19.8)	60 (10.2)	34 (12.6)	**< .001**
Bisexual	166 (11.3)	757 (40)	736 (35.3)	199 (34)	80 (29.7)	**< .001**
Gay	1,320 (89.6)	234 (12.3)	344 (16.5)	178 (30.4)	10 (3.7)	**< .001**
Lesbian	0 (0)	898 (47.3)	385 (18.7)	8 (1.4)	140 (52)	**< .001**
Pansexual	46 (3.1)	302 (15.9)	483 (23.2)	99 (16.9)	48 (17.8)	**< .001**
Queer	176 (12)	794 (41.8)	1,351 (64.8)	261 (44.5)	61 (22.7)	**< .001**
Questioning	9 (.6)	27 (1.4)	78 (3.7)	33 (5.6)	19 (7.1)	**< .001**
Same-gender loving	46 (3.1)	80 (4.2)	133 (6.4)	30 (5.1)	10 (3.7)	**< .001**
Straight/heterosexual	4 (.3)	8 (.4)	24 (1.2)	61 (10.4)	17 (6.3)	**< .001**
Two-spirit	4 (.3)	2 (.1)	27 (1.3)	1 (.2)	4 (1.5)	**< .001**
Another sexual orientation	9 (.6)	50 (2.6)	146 (7)	18 (3.1)	12 (4.5)	**< .001**
Selected more than one sexual orientation	254 (17.2)	946 (49.8)	1,287 (61.7)	252 (43)	117 (43.5)	**< .001**
Income level (*n, %*)						**< .001**
≤ $20,000	229 (17.1)	501 (29.5)	891 (47.7)	263 (49.5)	79 (32)	
$20,001 to $40,000	267 (20)	385 (22.7)	437 (23.4)	112 (21.1)	45 (18.2)	

$40,001 to $60,000	211 (15.8)	287 (16.9)	268 (14.3)	65 (12.2)	36 (14.6)	
≥ $60,001	631 (47.2)	523 (30.8)	272 (14.6)	89 (16.8)	87 (35.2)	
Education level (*n, %*)						**< .001**
No high school diploma	2 (.1)	7 (.4)	16 (.9)	9 (1.7)	1 (.4)	
High school/GED graduate or some college	236 (17.5)	270 (15.8)	538 (28.6)	204 (38.1)	70 (28.1)	
College degree (2- or 4-year)	504 (37.4)	647 (37.9)	802 (42.6)	198 (37)	108 (43.4)	
Graduate or Professional degree	606 (45)	784 (45.9)	525 (27.9)	124 (23.2)	70 (28.1)	
Geographic region (*n, %*)						**< .001**
Midwest	247 (17)	379 (20.3)	459 (22.5)	117 (20.5)	48 (18.2)	
Northeast	236 (16.2)	427 (22.9)	450 (22)	121 (21.2)	45 (17.1)	
South	475 (32.7)	432 (23.2)	490 (24)	162 (28.3)	96 (36.4)	
West	497 (34.2)	625 (33.6)	643 (31.5)	172 (30.1)	75 (28.4)	

[a.] Multiple answer choices were allowed.

Table 3

Demographic differences between participants who were classified by our algorithm into a gender identity category that was concordant versus discordant with their single category selection

Variable	Classification concordance (*N* = 5,646) (*n*, %)	Classification discordance (*N* = 585) (*n*, %)	*Odds Ratio (OR)*	*p*	*95% CI*
Age category			1.09	.164	(.96, 1.24)
18-30 years[a]	2,771 (89.2)	335 (10.8)			
31-45 years	1,623 (91.5)	151 (8.5)			
46-60 years	790 (94.3)	48 (5.7)			
61 years and older	462 (90.1)	51 (9.9)			
Race and ethnicity[b]					
American Indian or Alaska Native	173 (85.6)	29 (14.4)	1.70	.087	(.93, 3.10)
Asian	298 (91.1)	29 (8.9)	1.37	.311	(.75, 2.51)
Black, African American, or African	225 (88.9)	28 (11.1)	1.56	.115	(.90, 2.71)
Hispanic, Latino, or Spanish	406 (91.2)	39 (8.8)	1.22	.497	(.68, 2.20)
Middle Eastern or North African	76 (87.4)	11 (12.6)	**2.26**	**.033**	**(1.07, 4.77)**
Native Hawaiian or other Pacific Islander[c]	14 (100)	0 (0)	-	-	-
White	5,086 (90.6)	526 (9.4)	1.36	.238	(.82, 2.28)
None of these fully describe me	75 (82.4)	16 (17.6)	**2.41**	**.019**	**(1.16, 5.03)**
Selected more than one race and/or ethnicity	636 (89.3)	76 (10.7)	0.64	.157	(.34, 1.19)
Sexual orientation[b]					
Asexual	598 (89.8)	68 (10.2)	.92	.620	(.66, 1.28)
Bisexual	1,692 (88.4)	221 (11.6)	1.17	.228	(.91, 1.49)
Gay	1,908 (92.4)	157 (7.6)	.84	.181	(.66, 1.08)
Lesbian	1,277 (90.3)	137 (9.7)	1.14	.351	(.87, 1.48)
Pansexual	836 (86.1)	135 (13.9)	**1.35**	**.026**	**(1.04, 1.76)**
Queer	2,287 (87.4)	331 (12.6)	**1.57**	**.002**	**(1.19, 2.08)**
Questioning	135 (82.3)	29 (17.7)	1.50	.090	(.94, 2.39)
Same-gender loving	237 (81.2)	55 (18.8)	**1.67**	**.005**	**(1.17, 2.40)**
Straight/heterosexual	101 (90.2)	11 (9.8)	1.17	.633	(.62, 2.19)
Two-spirit	30 (78.9)	8 (21.1)	1.76	.243	(.68, 4.50)
Another sexual orientation	212 (91.8)	19 (8.2)	.65	.107	(.38, 1.10)

Selected more than one sexual orientation	2,465 (87.1)	366 (12.9)	1.33	.095	(.95, 1.86)
Income level			**.88**	**.009**	**(.80, .97)**
≤ $20,000[a]	1,732 (88.3)	229 (11.7)			
$20,001 to $40,000	1,121 (90)	124 (10)			
$40,001 to $60,000	789 (91)	78 (9)			
≥ $60,001	1,500 (93.7)	101 (6.3)			
Education level			**.85**	**.019**	**(.74, .97)**
No high school diploma[a]	31 (88.6)	4 (11.4)			
High school/GED graduate or some college	1,156 (87.7)	162 (12.3)			
College degree (2- or 4-year)	2,050 (90.9)	206 (9.1)			
Graduate or Professional degree	1,945 (92.4)	161 (7.6)			
Geographic region					
Midwest	1,117 (89.6)	130 (10.4)	**1.38**	**.016**	**(1.06, 1.80)**
Northeast	1,150 (90.1)	126 (9.9)	**1.27**	**.074**	**(.98, 1.66)**
South	1,500 (90.8)	152 (9.2)	1.22	.118	(.95, 1.56)
West[a]	1,837 (91.6)	169 (8.4)	-	-	-

[a.] Reference group.

[b.] Participants could select more than one option, thus answer choices for each identity were dichotomized to reported and did not report. For example, we compared participants who identified as asexual to those who did not identify with that specific identity. Percentage is reported as an overall total of concordance or discordance for each respective demographic characteristic.

[c.] Omitted from logistic regression because all participants who selected the identity were in a category concordant with their single category choice.

Figure 1

Methods for assessing gender identity in The PRIDE Study's 2020 Annual Questionnaire

Method #1: Expanded Choice Model

(Multiple selection with a write-in option)

What is your current gender identity? (Check all that apply.)

- ☐ Agender
- ☐ Cisgender man
- ☐ Cisgender woman
- ☐ Genderqueer
- ☐ Man
- ☐ Non-binary
- ☐ Questioning
- ☐ Transgender man
- ☐ Transgender woman
- ☐ Two-spirit
- ☐ Woman
- ☐ Another gender identity ___________________

Method #2: Reduced Choice Model

(Single selection with reduced, predefined answer choices)

If you had to choose only one of the following terms, which best describes your current gender identity?

("Cisgender" here means identifying with the sex assigned to you at birth. For example, a cisgender woman identifies as a woman and was assigned female sex at birth.)

- ◯ Cisgender man
- ◯ Cisgender woman
- ◯ Non-binary
- ◯ Transgender man
- ◯ Transgender woman
- ◯ Another gender identity

Figure 2

Examples of strings associated with the five gender identity-related terms

Cisgender
- "cis"

Feminine
- "fem"
- "girl"
- "lady"
- "wom"

Masculine
- "masc"
- "boy"
- "guy"
- "-man"

Non-binary
- "agen"
- "bigen"
- "gray"
- "neu"

Transgender
- "trans"

References

Bauer, G. R., Braimoh, J., Scheim, A. I., & Dharma, C. (2017). Transgender-inclusive measures of sex/gender for population surveys: Mixed-methods evaluation and recommendations. *PLOS ONE*, *12*(5), e0178043. https://doi.org/10.1371/journal.pone.0178043

Beaudry, J., Kothe, E., Singleton Thorn, F., McGuire, R., Tierney, N., & Ling, M. (n.d.). *gendercoder: Recodes Sex/Gender Descriptions into a Standard Set* [R package version 0.0.0.9000.]. Retrieved April 4, 2023, from https://github.com/ropenscilabs/gendercoder

Beischel, W. J., Schudson, Z. C., Hoskin, R. A., & van Anders, S. M. (2022). The gender/sex 3×3: Measuring and categorizing gender/sex beyond binaries. *Psychology of Sexual Orientation and Gender Diversity*, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/sgd0000558

Cahill, S., Singal, R., Grasso, C., King, D., Mayer, K., Baker, K., & Makadon, H. (2014). Do ask, do tell: High levels of acceptability by patients of routine collection of sexual orientation and gender identity data in four diverse American community health centers. *PloS One*, *9*(9), e107104. https://doi.org/10.1371/journal.pone.0107104

Callander, D., Newman, C. E., Holt, M., Rosenberg, S., Duncan, D. T., Pony, M., Timmins, L., Cornelisse, V., Duck-Chong, L., Wang, B., & Cook, T. (2021). The Complexities of Categorizing Gender: A Hierarchical Clustering Analysis of Data from the First Australian Trans and Gender Diverse Sexual Health Survey. *Transgender Health*, *6*(2), 74–81. https://doi.org/10.1089/trgh.2020.0050

Flentje, A., Barger, B. T., Capriotti, M. R., Lubensky, M. E., Tierney, M., Obedin-Maliver, J., & Lunn, M. R. (2020). Screening gender minority people for harmful alcohol use. *PLOS ONE*, *15*(4), e0231022. https://doi.org/10.1371/journal.pone.0231022

Institute of Medicine. (2011). *The Health of Lesbian, Gay, Bisexual, and Transgender People: Building a Foundation for Better Understanding*. The National Academies Press.

Kattari, S. K., Bakko, M., Langenderfer-Magruder, L., & Holloway, B. T. (2021). Transgender and Nonbinary Experiences of Victimization in Health care. *Journal of Interpersonal Violence*, *36*(23–24), NP13054–NP13076. https://doi.org/10.1177/0886260520905091

Kuper, L. E., Nussbaum, R., & Mustanski, B. (2012). Exploring the diversity of gender and sexual orientation identities in an online sample of transgender individuals. *Journal of Sex Research*, *49*(2–3), 244–254. https://doi.org/10.1080/00224499.2011.596954

Lefevor, G. T., Boyd-Rogers, C. C., Sprague, B. M., & Janis, R. A. (2019). Health disparities between genderqueer, transgender, and cisgender individuals: An extension of minority stress theory. *Journal of Counseling Psychology*, *66*(4), 385.

Lindqvist, A., Sendén, M. G., & Renström, E. A. (2021). What is gender, anyway: A review of the options for operationalising gender. *Psychology & Sexuality*, *12*(4), 332–344. https://doi.org/10.1080/19419899.2020.1729844

Lombardi, E., & Banik, S. (2016). The Utility of the Two-Step Gender Measure Within Trans and Cis Populations. *Sexuality Research & Social Policy : Journal of NSRC : SR & SP*, *13*(3), 288–296. https://doi.org/10.1007/s13178-016-0220-6

Lunn, M. R., Lubensky, M., Hunt, C., Flentje, A., Capriotti, M. R., Sooksaman, C., Harnett, T., Currie, D., Neal, C., & Obedin-Maliver, J. (2019). A digital health research platform for community engagement, recruitment, and retention of sexual and gender minority adults in a national longitudinal cohort study——The PRIDE Study. *Journal of the American Medical Informatics Association*, *26*(8–9), 737–748.

Measuring Sex, Gender Identity, and Sexual Orientation. (2022). National Academies Press. https://doi.org/10.17226/26424

Mehta, C. M., Arnett, J. J., Palmer, C. G., & Nelson, L. J. (2020). Established adulthood: A new conception of ages 30 to 45. *The American Psychologist*, *75*(4), 431–444. https://doi.org/10.1037/amp0000600

National Institutes of Health. (2024, January 29). *LGBTI-SafeZone Terminology | Office of Equity, Diversity, and Inclusion*. https://www.edi.nih.gov/people/sep/lgbti/safezone/terminology

Newcomb, M. E., Hill, R., Buehler, K., Ryan, D. T., Whitton, S. W., & Mustanski, B. (2019). High Burden of Mental Health Problems, Substance Use, Violence, and Related Psychosocial Factors in Transgender, Non-Binary, and Gender Diverse Youth and Young Adults. *Archives of Sexual Behavior*. https://doi.org/10.1007/s10508-019-01533-9

Obedin-Maliver, J., Hunt, C., Flentje, A., Armea-Warren, C., Bahati, M., Lubensky, M. E., Dastur, Z., Eastburn, C., Hundertmark, E., Moretti, D. J., Pho, A., Rescate, A., Greene, R. E., Williams, J. T., Hursey, D., Cook-Daniels, L., & Lunn, M. R. (2024). Engaging Sexual and Gender Minority (SGM) Communities for Health Research: Building and Sustaining PRIDEnet. *Journal of Community Engagement and* Scholarship, *16*(2), 1–34. https://doi.org/10.54656/jces.v16i2.484

Ocasio, M. A., Fernandez, M. I., Ward, D. H. S., Lightfoot, M., Swendeman, D., & Harper, G. W. (2024). Fluidity in Reporting Gender Identity Labels in a Sample of Transgender and Gender Diverse Adolescents and Young Adults, Los Angeles, California, and New Orleans, Louisiana, 2017-2019. *Public Health Reports*, 00333549231223922. https://doi.org/10.1177/00333549231223922

Patterson, J. G., Jabson, J. M., & Bowen, D. J. (2017). Measuring Sexual and Gender Minority Populations in Health Surveillance. *LGBT Health*, *4*(2), 82–105. https://doi.org/10.1089/lgbt.2016.0026

Puckett, J. A., Brown, N. C., Dunn, T., Mustanski, B., & Newcomb, M. E. (2020). Perspectives from transgender and gender diverse people on how to ask about gender. *LGBT Health*, *7*(6), 305–311.

R Core Team. (2023). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/.

Reisner, S. L., Biello, K., Rosenberger, J. G., Austin, S. B., Haneuse, S., Perez-Brumer, A., Novak, D. S., & Mimiaga, M. J. (2014). Using a Two-Step Method to Measure Transgender Identity in Latin America/the Caribbean, Portugal, and Spain. *Archives of Sexual Behavior*, *43*(8), 1503–1514. https://doi.org/10.1007/s10508-014-0314-2

Reisner, S. L., Conron, K. J., Scout, Baker, K., Herman, J. L., Lombardi, E., Greytak, E. A., Gill, A. M., & Matthews, A. K. (2015). "Counting" Transgender and Gender-Nonconforming Adults in Health Research: Recommendations from the Gender Identity in US Surveillance Group. *TSQ: Transgender Studies Quarterly*, *2*(1), 34–57. https://doi.org/10.1215/23289252-2848877

Reisner, S. L., Conron, K. J., Tardiff, L. A., Jarvi, S., Gordon, A. R., & Austin, S. B. (2014). Monitoring the health of transgender and other gender minority populations: Validity of natal sex and gender identity survey items in a U.S. national cohort of young adults. *BMC Public Health*, *14*(1), 1224. https://doi.org/10.1186/1471-2458-14-1224

Ridolfo, H., Miller, K., & Maitland, A. (2012). Measuring Sexual Identity Using Survey Questionnaires: How Valid Are Our Measures? *Sexuality Research and Social Policy*, *9*(2), 113–124. https://doi.org/10.1007/s13178-011-0074-x

Scheffey, K. L., Ogden, S. N., & Dichter, M. E. (2019). "The Idea of Categorizing Makes Me Feel Uncomfortable": University Student Perspectives on Sexual Orientation and Gender Identity Labeling in the Healthcare Setting. *Archives of Sexual Behavior*, *48*(5), 1555–1562. https://doi.org/10.1007/s10508-019-1401-1

StataCorp. 2021. Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC. (n.d.). [Computer software].

Suen, L. W., Lunn, M. R., Katuzny, K., Finn, S., Duncan, L., Sevelius, J., Flentje, A., Capriotti, M. R., Lubensky, M. E., Hunt, C., Weber, S., Bibbins-Domingo, K., & Obedin-Maliver, J. (2020). What Sexual and Gender Minority People Want Researchers to Know About Sexual Orientation and

Gender Identity Questions: A Qualitative Study. *Archives of Sexual Behavior*, *49*(7), 2301–2318. https://doi.org/10.1007/s10508-020-01810-y

Tate, C. C., Ledbetter, J. N., & Youssef, C. P. (2013). A two-question method for assessing gender categories in the social and medical sciences. *Journal of Sex Research*, *50*(8), 767–776. https://doi.org/10.1080/00224499.2012.690110

The Gender Identity in U.S. Surveillance (GenIUSS) Group. (2014). *Best Practices for Asking Questions to Identify Transgender and Other Gender Minority Respondents on Population-Based Surveys* (J.L. Herman, Ed.). The Williams Institute. https://williamsinstitute.law.ucla.edu/wp-content/uploads/Survey-Measures-Trans-GenIUSS-Sep-2014.pdf

Tordoff, D. M., Morgan, J., Dombrowski, J. C., Golden, M. R., & Barbee, L. A. (2019). Increased Ascertainment of Transgender and Non-binary Patients Using a 2-Step Versus 1-Step Gender Identity Intake Question in an STD Clinic Setting. *Sexually Transmitted Diseases*, *46*(4), 254–259. https://doi.org/10.1097/OLQ.0000000000000952

Vivienne, S., Hanckel, B., Byron, P., Robards, B., & Churchill, B. (2021). The social life of data: Strategies for categorizing fluid and multiple genders. *Journal of Gender Studies*, *0*(0), 1–16. https://doi.org/10.1080/09589236.2021.2000852

Wilson, B. D. M., & Meyer, I. H. (2021). *Nonbinary LGBTQ Adults in the United States*. https://williamsinstitute.law.ucla.edu/publications/nonbinary-lgbtq-adults-us/

Young, S. K., & Bond, M. A. (2023). A scoping review of the structuring of questions about sexual orientation and gender identity. *Journal of Community Psychology*, *51*(7), 2592–2617. https://doi.org/10.1002/jcop.23048