A Framework for More Intentional and Equity-Minded Race Data Disaggregation

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Abstract

Higher education leaders have repeatedly called for improved diversity, equity, and inclusion efforts, but many institutions continue to fall short. Data can play an integral role in this work; key among them are data on student demographics, including race/ethnicity. Meeting diversity, equity, and inclusion goals requires a thorough and nuanced understanding of the diversity within student bodies through intentional and systematic data disaggregation from broad racial/ethnic categories (e.g., Asian American, Black or African American [hereafter Black], Latinx) into finer subgroups (e.g., Hmong, Haitian, Salvadoran). Without further data disaggregation, minoritized student populations can remain invisible to institutional leaders who seek to provide focused, targeted equity programming. To offer actionable guidance for race data disaggregation, we present a case study on the Asian Pacific Islander Desi American (APIDA) undergraduate population at a large public university in the Southwest United States as a roadmap for institutions seeking to further disaggregate student race/ethnicity data. APIDA students are often homogenized as a group that has been very successful in higher education; our case study, however, found significant heterogeneity in demographic profiles and academic outcomes, showing that this model minority myth belies tremendous diversity within the group. When disaggregated into regional and national origin groups, the APIDA population demonstrates first-generation college status and Pell Grant (hereafter Pell) eligibility proportions, as well as 1st-year GPA and 2nd-year

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retention rates, that range from the lowest to the highest at the university level across all racial/ethnic groups. Building on the insights gained, we present a Race Data Disaggregation Readiness framework to contextualize the continuum of readiness of postsecondary institutions to do this work, and we offer suggestions on how they can progress—or level up—in their readiness.

Keywords: data disaggregation, race/ethnicity, Asian Pacific Islander Desi American, demographic profiles, academic outcomes

INTRODUCTION

The collection of racial/ethnic data in higher education—when done intentionally with an equity lens—can be an important tool in developing evidence-based practices for student success. Postsecondary institutions rely on racial/ethnic data to identify patterns across a host of demographic, academic, and institutional indicators, advocate for the allocation of resources, and develop data-driven programs to promote important goals, such as student retention, graduation rates, and general improvement in academic performance. Many of these institutions, however, rely on broad pan-ethnic categories, such as Latinx, Asian American, Native American, or Native Hawaiian and Pacific Islander, to classify students' racial/ethnic backgrounds. This practice can obscure important variations within these groups, which can lead to gross overgeneralizations, perpetuation of stereotypes, and the spread of common misconceptions harmful to students.

The tendency to use pan-ethnic categories by postsecondary institutions has led many—including administrators, faculty, and students—to advocate for the collection of disaggregated racial/ethnic student data into finer subgroups (e.g., Thai, Jamaican, Mexican; see Kauh et al., 2021). Progress has been slow, however, and many postsecondary institutions have yet to make significant changes to their current data collection practices.

To address these critical issues, we use a case study of the Asian Pacific Islander Desi American (APIDA)[1] student population at a large, regional public university in Southern California to make a case for disaggregating beyond pan-ethnic groups. Our findings reveal significant heterogeneity within the APIDA student population, demonstrating the importance of race data disaggregation to expose disparities that are often overlooked within broad racial/ethnic groups. Furthermore, our case study illustrates a systematic approach that can be used to achieve more intentional and equity-minded race data disaggregation. Building on insights gained from conducting the case study, we offer a framework for data disaggregation readiness. More specifically, we provide actionable suggestions for postsecondary institutions to progress—or level up—in their readiness based on their access to disaggregated data, analytic approach, and dissemination strategies, while also recognizing distinct institutional and resource-related challenges that administrators may navigate along the way. Considerations for data confidentiality, regrouping disaggregated data with intention, and analyzing and presenting disaggregated data are discussed. With this article we strive to offer best practices that are both grounded in real-world experiences and that have implications for postsecondary institutions promoting academic success among students belonging to diverse racial/ethnic groups.

1. In this paper, we intentionally use the term *APIDA* to highlight the inclusion of South Asians/Desis, who are often overlooked in the Asian American diaspora.

ASIAN PACIFIC ISLANDER DESI AMERICANS

The APIDA population is one of the most culturally, socioeconomically, and politically diverse (and is among the fastest-growing) racial/ethnic groups in the United States. The APIDA population saw an 81% increase in size between 2000 and 2019 (Budima & Ruiz, 2021a). If this trend continues, the APIDA population is projected to triple by 2060, surpassing the Latinx group for the first time (Budima & Ruiz, 2021b).

There are many terms used to represent this diverse population, such as Asian American Pacific Islander, and Asian American and Native Hawaiian and Pacific Islander. In this article, we intentionally use APIDA to highlight the inclusion of South Asians/Desis, who are often overlooked in the Asian American diaspora. APIDA as a pan-ethnic term represents a diverse number of ethnic groups from East Asia (e.g., Chinese, Korean, Japanese), South Asia (e.g., Indian, Bangladeshi, Sri Lankan), Southeast Asia (e.g., Filipino, Hmong, Viet), and the islands of Melanesia (e.g., Fijian, Papua New Guinean, Solomon Islander), Micronesia (e.g., Chamorro/Guamanian, Mariana Islander, Saipanese), and Polynesia (e.g., Native Hawaiian, Samoan, Tahitian). Each ethnic group has its own unique historical contexts, migration patterns, and racialization, contributing to the diverse lived experiences within these communities.

Some APIDA ethnic groups have primarily immigrated to the United States for career and educational opportunities, whereas others sought asylum in the United States due to political instability in their home countries. For example, the first wave of Asian immigration consisted of Chinese, Japanese, Filipino, and, to a lesser extent, Korean laborers in the late 19th and early 20th centuries. However, Congress—motivated by racial animus—placed several bans on Asian immigrants; an example is the National Origins Act of 1924, passed to ensure the United States population remained European. The Immigration and Nationality Act of 1965 and the Immigration Act of 1990 put an end to these exclusionary immigration policies and placed greater emphasis on attracting highly skilled immigrants, leading to hyper-selective immigration from Asia, particularly Chinese, Indian, Korean, and Filipino individuals who immigrated to the United States for work and education opportunities (Tran et al., 2019; Zhou & Lee, 2017). In contrast, some APIDAs (such as Viet, Hmong, Khmer, and Lao Americans) are refugees from war-affected countries that were influenced by U.S. political involvement and other colonial forces, who may lack the economic resources, education, and English literacy to adapt smoothly to American life (Ngo & Lee, 2007; Southeast Asia Resource Action Center, 2020).

These diverse immigration patterns play a crucial role in understanding the socioeconomic heterogeneity within the APIDA community. For instance, ethnic groups like Indian (75%), Chinese (57%), and Korean (57%) exhibit higher bachelor's degree attainment rates, whereas groups such as Lao (18%), Hmong (23%), and Viet (32%) have comparatively lower rates (Budima & Ruiz, 2021b). When the aggregated bachelor's degree attainment of 54% for Asian Americans is presented alone, however, it masks these within-group differences. As such, although collecting students' racial/ethnic identity data helps educators to understand opportunity gaps and to develop programs to promote student outcomes, the reliance on aggregated data obscures diversity within the APIDA student population. The danger of making sweeping generalizations from aggregated data can lead faculty, administrators, and lawmakers to assume that all APIDA students are high achievers and "problem-free" (Museus & Chang, 2009; Shih et al., 2019), fostering the misconception that resources and institutional programming are unnecessary for this demographic. Therefore, to ensure APIDA students and students of other minoritized racial/ethnic groups are seen and represented, higher education institutions must move beyond the broad racial/ethnic categorizations commonly used and must systematically and intentionally disaggregate race data.

A CALL FOR DATA DISAGGREGATION

Given the aforementioned challenges, there have been numerous calls from academics, government leaders, and civic organizations to collect disaggregated data on APIDA students and students belonging to other racial/ethnic groups in postsecondary institutions (Chang et al., 2015; Ramakrishnan & Ahmad, 2014; Southeast Asia Resource Action Center, 2022). One method of data disaggregation is to deconstruct the common term—*underrepresented minorities* (URM)—into distinct pan-ethnic groups: Black, Latinx, and Native American. In this article, we take it a step further by using detailed ethnicity or national origin subgroups (e.g., Hmong, Haitian, Salvadoran). Our method also entails the collection of additional demographic characteristics by pan-ethnic group and subgroup, such as first-generation status, gender identity, and socioeconomic status. When intentionally implemented, data disaggregation can help faculty and administrators to identify students who have historically been overlooked and redirect vital campus resources (e.g., financial assistance, academic advisement, mental health services) to promote parity and close achievement gaps.

All postsecondary institutions that receive federal financial aid are required to collect and report racial/ethnic data about their students to the Integrated Postsecondary Education Data System (IPEDS).[2] According to IPEDS standards, to assess students' race and ethnicity, these postsecondary institutions, at a minimum, must use a two-part question (National Center for Education Statistics, n.d.). The first question asks about students' ethnicity: "Are you Hispanic or Latino?" The second question asks if students belong to one or more of the following racial groups: "American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, White." Although IPEDS allows institutions to add additional questions to disaggregate race data, it is up to the individual institution to do so, and only the aggregated form is mandatory for reporting purposes. This federal policy raises a key issue: the loose requirements can impede buy-in and disincentivize systematic race data disaggregation across institutions.

The current landscape in higher education must move beyond standard aggregate measures to improve their understanding of racial equity, diversity, and inclusion on their campuses. We now turn to a case study of disaggregated data on the APIDA student population at our university to showcase key insights that are obscured when the data are presented only in the aggregate form. More importantly, we provide a detailed account of our procedure, which serves as a roadmap for other institutions looking to implement race data disaggregation.

2. There are nearly 6,000 postsecondary institutions that accept federal financial aid.

CASE STUDY

In this case study, we disaggregated data on the APIDA undergraduate student population at California State University, Northridge (CSUN). CSUN is a large, regional, masters-level public university in the San Fernando Valley region of Los Angeles County. CSUN is a part of the California State University (CSU) system. The CSU system is the nation's largest and most diverse public university system, comprising 23 campuses across California. CSUN has consistently been among the five largest CSU campuses based on student head count (CSU, n.d.b). In 2021, the university served a total of 34,275 undergraduate students, 71.4% of them being first-generation and 56.8% Pell recipients. The four largest racial/ethnic groups that year were Latinx (56.9%), White (20.5%), APIDA (9.1%), and Black (4.7%) (CSUN Counts, n.d.). CSUN holds the designation of being a Hispanic-serving institution and was previously an Asian American and Native American Pacific Islander–serving institution. The many ethnic and national origin groups within the APIDA community make it a compelling pan-ethnic case study to showcase the process and benefits of race data disaggregation.

Data Overview

Applicants to all CSU campuses, including CSUN, must complete the CSU systemwide common application (Cal State Apply; CSU, n.d.a). This form includes the two IPEDS-required questions about race/ethnicity, as well as additional options to specify detailed ethnic and national origin identity under each of the pan-ethnic racial/ethnic groups (see Cal State Apply [CSU, n.d.a] for a comprehensive list of available options). Applicants can choose from among 49 detailed APIDA ethnic and national origin identities.

For our case study, we used the detailed race/ethnicity data collected from the CSU system common application for undergraduate applicants to CSUN (first-time freshmen and new undergraduate, upper-division transfers) from 2009 to 2021. After filtering for only APIDA-identifying students who are not international students (i.e., those who hold F and J visas),[3] the dataset includes 13,396 students, representing 28 APIDA ethnicities of the 49 options on the Cal State Apply form.[4] In addition to data on race/ethnicity, the dataset contains additional demographic characteristics, including parents' education and Pell eligibility, as well as academic outcomes, such as 1st-year GPA and retention rates.

DISAGGREGATION TO REGIONAL GROUPINGS AS A STRATEGY

The CSU application, from which we are pulling data for this case study, includes 49 detailed APIDA ethnic and national origin identities. This many categories, which include some groups with very small counts, can be overwhelming; it can be difficult to develop a cohesive data story due to the diverse number of individual trends and patterns that require interpretation. Recognizing the need for a more manageable approach, we regrouped the disaggregated APIDA ethnic and national origin data into regional Asian and Pacific Islander groups as informed by the Asian Pacific Institute on Gender-Based Violence (n.d.) with two modifications: (1) the Filipino ethnic group was disaggregated from the Southeast Asia region into its own separate category due to its unique history with U.S. colonization

3 . Research suggests variation in demographics and academic outcomes between domestic and international students.

4 . Some APIDA ethnic groups might not be represented in this case study due to the limited options provided in the CSU system common application form and enrollment patterns at CSUN.

(David & Okazaki, 2006) and its relatively large size at CSUN; and (2) due to the shared sociopolitical identity as refugees following the Vietnam War, Khmer Rouge Genocide in Cambodia, and the U.S. Secret War in Laos (Southeast Asia Resource Action Center, 2020), the Khmer, Hmong, Lao, and Viet ethnic groups are grouped as one-half of the Southeast Asia region, while the remaining ethnic groups in the Southeast Asia region are grouped separately: Burmese, Indonesian, Indo Chinese, Malaysian, Singaporean, and Thai. See Table 1 for the regional groupings.

Table 1. Disaggregated Regional Groupings

Regional Group	Detailed Ethnicity or National Origin	
East Asian	• Chinese • Iwo Jiman • Japanese	• Korean • Okinawan • Taiwanese
Filipino	• Filipino	
Native Hawaiian and Pacific Islander	• Carolinian • Chuukese • Fijian • Chamorro/ Guamanian • I-Kiribati • Kosraean • Mariana Islander • Marshallese • Native Hawaiian • Ni-Vanuatu	• Palauan • Papua New Guinean • Pohnpeian • Saipanese • Samoan • Solomon Islander • Tahitian • Tokelauan • Tongan • Yapese
South Asian/Desi	• Bangladeshi • Bhutanese • Indian • Maldivian	• Nepalese • Pakistani • Sri Lankan
Southeast Asian 1: Refugees	• Khmer • Hmong	• Lao • Viet
Southeast Asian 2: Geography	• Burmese • Indonesian • Indo Chinese	• Malaysian • Singaporean • Thai

The strategy of pulling out the larger ethnic or national origin groups, such as Filipinos in our case, and grouping the smaller groups by region is a common practice in APIDA scholarship and work, since it helps with increasing group sizes and strengthening data confidentiality (CARE, 2015; Nguyen et al., 2018). This approach could be adopted at other institutions as well, particularly those with smaller APIDA student populations. This grouping assumes that ethnic subgroups in regions of Asia and the Pacific Islands share similarities in immigration histories and racialized experiences. The decision to pull out specific ethnic groups, however, also acknowledges the unique characteristics within these regional similarities that warrant individual analyses, especially if the group is large enough. We present the sociopolitical and regional groupings here as one possibility and recommend that other institutions consider groupings that make sense in their context. Importantly, we acknowledge that there is no one right way to determine which groups and how many groups to use in APIDA disaggregation work. We revisit this topic later in the "Discussion" section of the article, where we also elaborate on additional considerations for decision-making.

Enrollment Count

CSUN serves a diverse APIDA undergraduate population from varying regional and ethnic groups. During the period under study, Filipino students comprised the largest APIDA ethnic group, making up 38.33% of the APIDA population at CSUN. The next-largest regional groups were East Asian students at 28.05%, South Asian/Desi (12.77%), Southeast Asian 1: Refugees (11.23%), Southeast Asian 2: Geography (4.55%), and Native Hawaiian and Pacific Islander (1.25%). Approximately 3.81% of the APIDA undergraduate student body selected "Other Asian," "Decline to State," "Not Specified," or "Two or More Ethnicities." The five largest ethnic groups at CSUN by head count during the period under study were Filipino (5,135), Korean (1,813), Chinese (1,328), Viet (1,276), and Indian (873). See Table 2 for a breakdown of student count by regional grouping and ethnicity.

Table 2. New Asian Pacific Islander Desi American Undergraduate Enrollments, 2009–2021

	Count	APIDA Percentage
East Asian	3,757	28.0%
Korean	1,813	13.5%
Chinese	1,328	9.9%
Japanese	405	3.0%
Taiwanese	205	1.5%
Filipino	5,135	38.3%
Native Hawaiian and Pacific Islander	168	1.3%
Other Pacific Islander	69	0.5%
Guamanian/Chamorro	23	0.2%
Samoan	25	0.2%
Fijian	20	0.1%
Native Hawaiian	18	0.1%
Tongan	12	0.1%

	Count	APIDA Percentage
South Asian/Desi	1,711	12.8%
Indian	873	6.5%
Pakistani	332	2.5%
Bangladeshi	287	2.1%
Sri Lankan	172	1.3%
Nepalese	46	0.3%
Southeast Asian 1: Refugees	1,505	11.2%
Viet	1,276	9.5%
Khmer	162	1.2%
Lao	35	0.3%
Hmong	32	0.2%
Southeast Asian 2: Geography	610	4.6%
Thai	396	3.0%
Indonesian	123	0.9%
Burmese	42	0.3%
Indo Chinese	32	0.2%
Other Asian	510	3.8%
APIDA	13,396	100%

Note: Some detailed ethnicity groups are not shown due to counts being hidden for groups with fewer than 10 individuals.

Because race data disaggregation involves breaking down pan-ethnic groupings into smaller subgroups, the granular data introduce potential data reidentification. In other words, because of the smaller group sizes it might become easier to trace and identify individual students. Consequences of data identifiability can be severe, including breaches of privacy, potential misuse of sensitive information, and violations of data security regulations. Therefore, steps must be taken to safeguard student data and reduce risks of reidentification. We choose to, and recommend, hiding groups smaller than 10 for these reasons. A potential workaround to allow the data from smaller ethnic groups to remain visible, however, is by intentionally grouping them with other ethnicities that have conceptual reasons to be similar—in our case, by regions informed by immigration histories. This highlights another functional aspect of the practice of grouping disaggregated data. Further considerations for data confidentiality when engaging in race data disaggregation will be discussed later in the article.

Between-Region and Within-Region Comparisons

By first regrouping the disaggregated APIDA data into regional groups, we gained a framework to make between-regional and within-regional APIDA group comparisons among the CSUN APIDA undergraduate population. In other words, instead of comparing APIDA students solely against White and other major racial/ethnic groups, the data structure with APIDA regional groupings established a framework for conducting more-meaningful and more-purposeful comparisons within the APIDA student population itself. This two-tiered between-region and within-region methodology enabled us to explore variations in demographics and academic outcomes across APIDA regional groups, compare them with other racial/ethnic groups, and delve into specific regional contexts. This approach provides a more detailed and contextually rich analysis of the APIDA undergraduate experience at CSUN, and this model could be used with data on other pan-ethnic racial/ethnic groups, such as Latinx and Black students. For example, among our Latinx population at CSUN, the three largest national origin groups are Guatemalan, Mexican, and Salvadoran, so we have begun to disaggregate those groups out, along with South American, other Central American, Caribbean, and other Latinx/Hispanic, in much the same way we have demonstrated for the APIDA case study.

Analytic Plan

We explored descriptive variations in demographic profiles (first-generation college status and Pell eligibility) and academic outcomes (1st-year GPA and 2nd-year retention rate) in the disaggregated data for CSUN APIDA undergraduate students. To address challenges related to statistical power and data confidentiality posed by small group sizes resulting from disaggregation, we chose to include cohort data from new students entering the university between Fall 2009 and Fall 2021.

We began by comparing the APIDA regional groups with Black, Latinx, and White students at CSUN, as well as with the APIDA aggregate (the four largest pan-ethnic groups) to provide a broader context for the findings. Subsequently, we disaggregated the data further into detailed APIDA ethnicity groups to investigate within-region differences. Finally, when analyzing academic outcomes, we split the data further by comparing first-time freshman and transfer student outcomes at the regional and detailed ethnicity levels to explore differences by disaggregated student entry type.

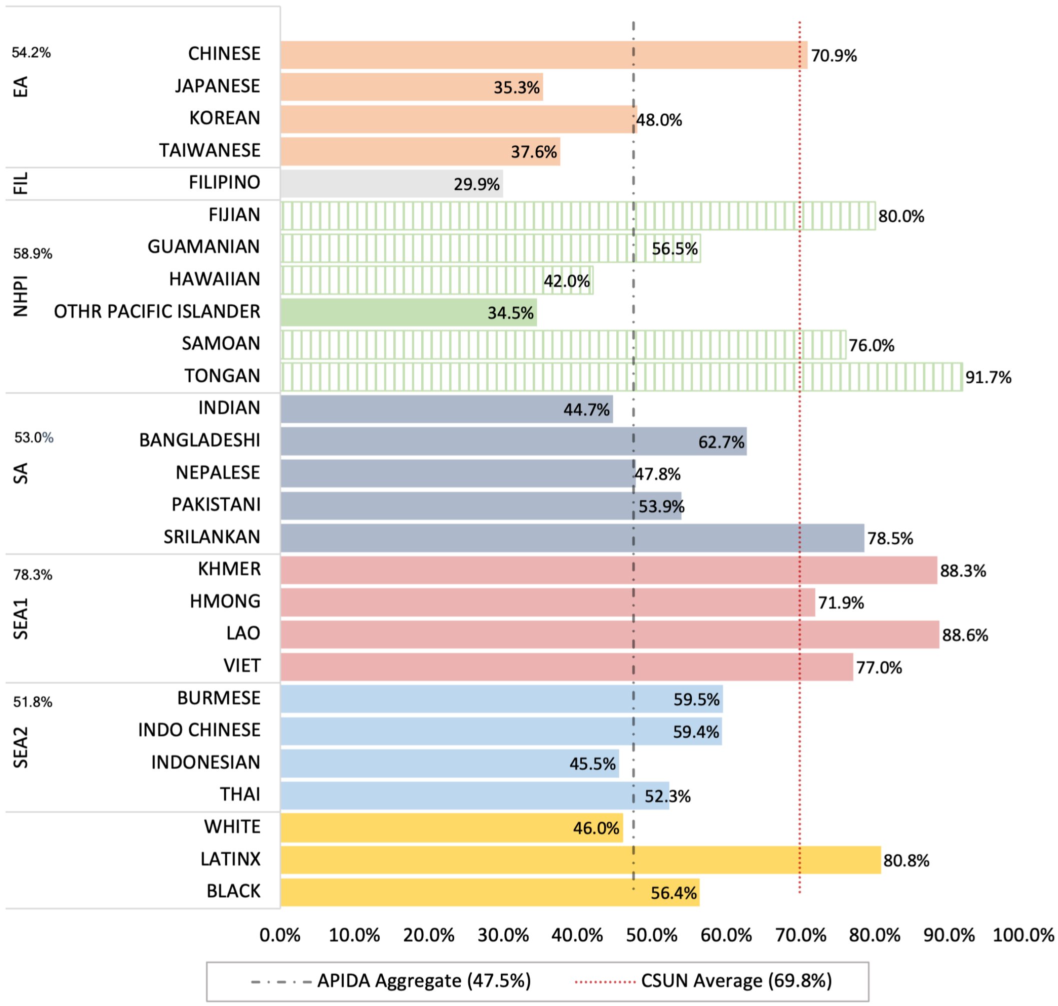
To help with interpretation of the disaggregated data, we used a visual approach through a series of bar graphs. We used two vertical lines for comparison, representing the aggregated 2009 to 2021 cohort data: the first line was for the comparison to numbers for the overall CSUN new undergraduate population, and the second was for the numbers for the aggregate APIDA CSUN new undergraduate population. This visualization method, another recommended practice resulting from this work, facilitates identification of disaggregated APIDA regional groups as well as detailed ethnicities that differ from these aggregated group proportions or mean scores. It also enables the exploration of differences among regional groups, racial/ethnic groups, within regional groups, and between different student types. Detailed ethnicity groups with fewer than 10 members were excluded, and those with 10 to 30 members were represented with striped bars. Interpretations for the latter should be approached with caution due to the small group sizes.

Demographic Profiles

APIDA students are a diverse population with varying demographic profiles influencing their academic journeys, yet the APIDA aggregate often conceals this diversity (Museus & Chang, 2009). A disaggregated understanding of these varied profiles is crucial for developing targeted institutional programs that can effectively meet the unique needs of the APIDA student body. In this section, we present the proportion of new undergraduates who were first-generation college students and Pell recipients at CSUN in each of the APIDA regional groups. We compare these students to the proportions in the APIDA aggregate, as well as with Black, Latinx, and White students (the four largest pan-ethnic groups), and compare them to the university average. Additionally, we examine ethnic comparisons within the regional groups themselves.

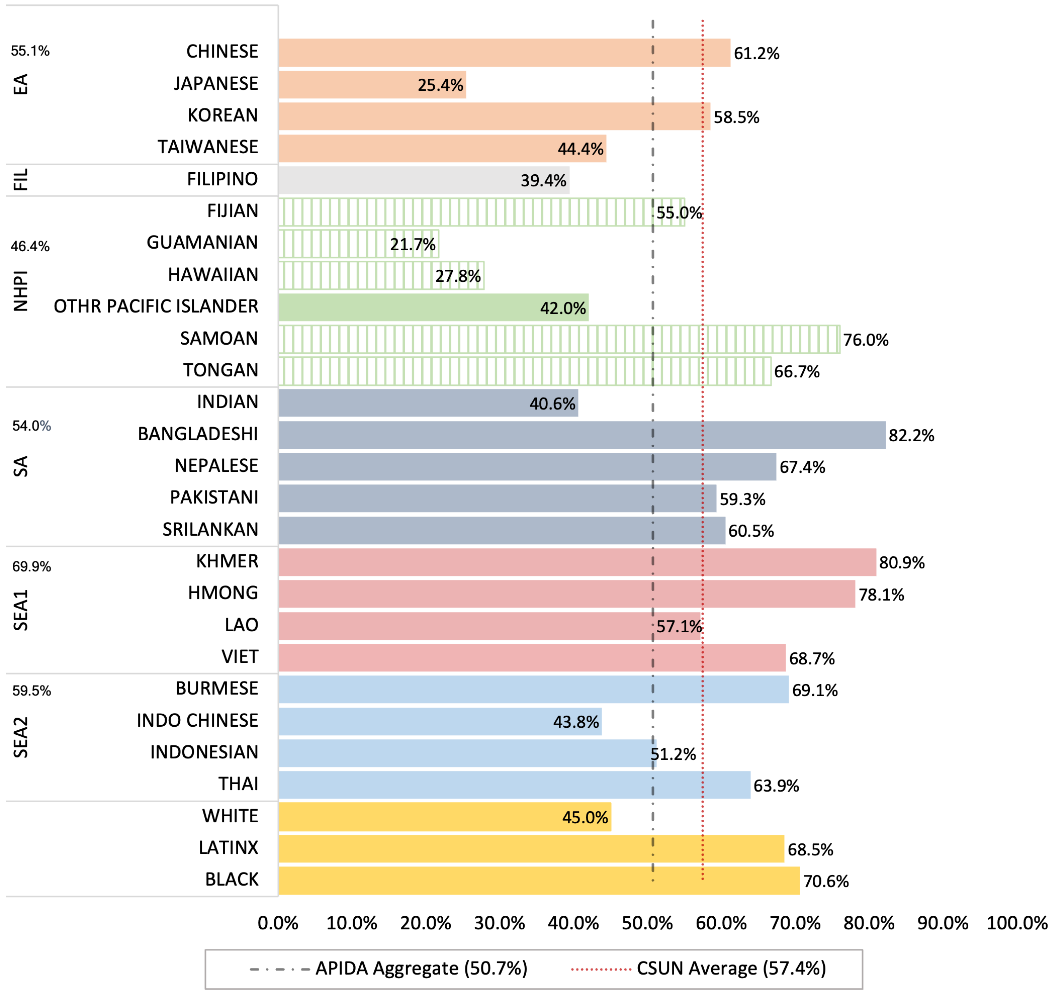
At the aggregate level, APIDA students were less likely to be first-generation college students (47.5%) or Pell recipients (50.7%) compared with their Latinx and Black peers (see Figures 1 and 2). These aggregate numbers, however, obscure the substantial variation in first-generation and Pell recipient status within the APIDA undergraduate population by regional group. For example, among all regional APIDA groups, the proportion of first-generation college students is higher than that of the APIDA aggregate, with the exception of Filipino students. Given that Filipino students represent the largest student count within the APIDA group, their lower rate of first-generation status (29.9%) seems to be driving the overall APIDA average down. In fact, the Southeast Asian 1: Refugees regional group (78.3%) showed a first-generation rate above the CSUN campus average (69.8%). Moreover, Southeast Asian 1: Refugees (69.9%) and Southeast Asian 2: Geography (59.5%) both had Pell eligibility proportions above the CSUN average (57.4%). Most notably, the Southeast Asian 1: Refugees region had the highest proportion of Pell-eligible students across the APIDA undergraduate population at the university and was more similar to the proportions of Latinx (68.9%) and Black (70.9%) students.

Figure 1. Proportion of First-Generation Students among New Asian Pacific Islander Desi American Undergraduate Students, 2009–2021



Note: EA = East Asian; FIL = Filipino; NHPI = Native Hawaiian and Pacific Islander; SA = South Asian/Desi; SEA1 = Southeast Asian 1: Refugee; SEA2 = Southeast Asian 2: Geography.

Figure 2. Proportion of Pell-Recipient Students among New Asian Pacific Islander Desi American Undergraduate Students,2009–2021



Note: EA = East Asian; FIL = Filipino; NHPI = Native Hawaiian and Pacific Islander; SA = South Asian/Desi; SEA1 = Southeast Asian 1: Refugee; SEA2 = Southeast Asian 2: Geography.

When the regional groupings were further disaggregated by detailed ethnicity, many ethnic groups showed higher proportions of first-generation status and Pell eligibility than the overall APIDA aggregate at the university. This serves as another example highlighting how the APIDA aggregate—and pan-ethnic groupings generally—can mask the diverse experiences within the finer ethnic groupings.

Furthermore, sizable variations exist between ethnic groups even within regional categories. For instance, within the East Asian regional group, the overall first-generation rate was 54.2%. However, this might not accurately represent the East Asian community at the university when we compare Japanese students (35.3%) and Chinese students (70.9%). Similarly, within the South Asian/Desi regional group, the overall Pell-recipient proportion was 54.0%, yet comparing Indian students (40.6%) to Bangladeshi students (82.2%) highlights notable within-region differences. Taken together, these findings (see Figures 1 and 2) also underscore the importance and need for detailed disaggregation to capture the nuanced differences and consistencies within the APIDA community.

Academic Outcomes

The false yet widely held belief that all APIDA students are academically successful and well-adjusted (Yoo et al., 2010) perpetuates the assumption that APIDA students do not require tailored institutional programming or resources (Shih et al., 2019). As showcased, APIDA students comprise diverse demographic profiles, some more resourced and some less resourced, which may influence diverse academic trajectories. Therefore, it is important for institutions to intentionally disaggregate their APIDA student data to understand the diverse academic outcomes of this population to better implement equitable academic programming. In this section, we focus on 1st-year GPA and 2nd-year retention, both of which serve as early predictors of academic adjustment (Larose et al., 2019).

We examined student outcome data by entry type, differentiating between first-time freshmen and transfer students. We then analyzed their disaggregated average 1st-year GPA and 2nd-year retention rates, comparing the results across regional groups, the APIDA aggregate, as well as Black, Latinx, and White students, and the university average. Similarly, we examined within-ethnic regional group comparisons.

As an aggregate, both APIDA freshmen (2.85) and transfers (2.89) demonstrated higher overall 1st-year GPAs than their Black and Latinx peers, but lower GPAs than their White peers. A similar pattern emerged in the retention rates for both freshman (85.1%) and transfer (86.0%) APIDA students, although the difference was not as pronounced.

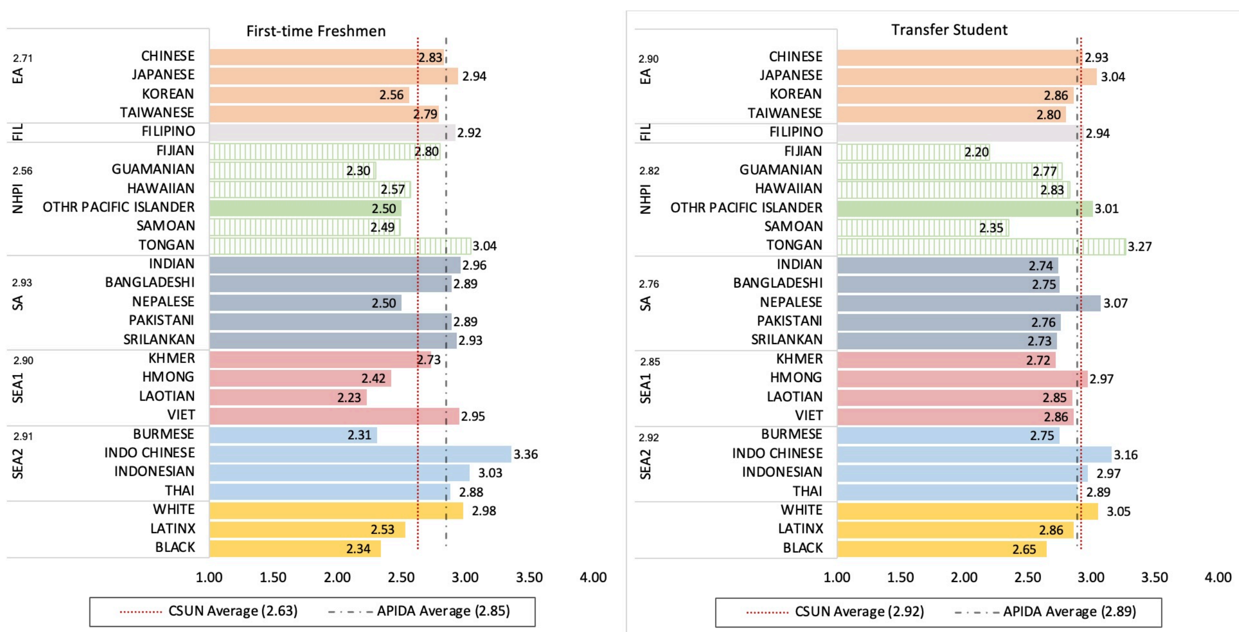
Consistent with the demographic profiles, notable variations were observed across APIDA regional groups. Within these groups, Native Hawaiian and Pacific Islander students exhibited the lowest average 1st-year GPA of all APIDA freshmen (2.56). Additionally, for both freshman and transfer Native Hawaiian and Pacific Islander students, their 2nd-year retention rates (75.5% and 71.9%, respectively) were lower than the university and APIDA averages. Furthermore, the retention rates for these transfer students were lower than those for Black and Latinx transfer students.

Differences also emerged among APIDA regional groups by student entry type. Notably, South Asian/Desi freshmen had the highest average 1st-year GPA (2.93) among the freshman APIDA students by regional groups. However, South Asian/Desi transfers had the lowest average 1st-year GPA (2.76) among the transfer APIDA students by regional groups, placing below both the CSUN and the APIDA aggregate averages.

Upon further disaggregation of the data to detailed ethnicity, more variations became evident. At the within-region level for freshmen, all the ethnic groups within the East Asian regional group had an overall average 1st-year GPA higher than the university average (2.63), except Korean students (2.56). Additionally, when it comes to retention rates, all East Asian freshmen showed rates above the university average (78.5%), except Korean students (77.4%). In other words, the academic outcomes of freshman Korean students may be obscured by the East Asian aggregate.

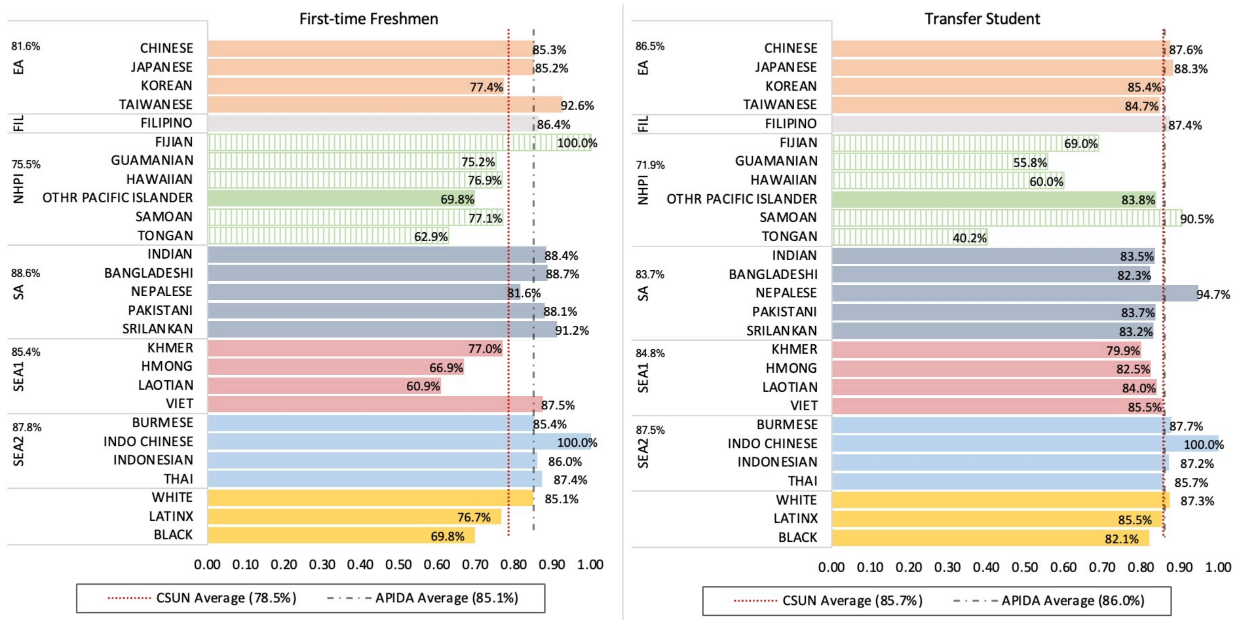
Although the variations are less pronounced among new APIDA transfer students, regional group patterns remain relatively consistent across student entry types. For example, within the Southeast Asian 1: Refugees regional group, Khmer, Hmong, and Lao freshmen and transfers show a lower retention rate than both the APIDA and university aggregate. Differences also emerged within detailed ethnicity by student entry type. Interestingly, Indian and Viet freshmen displayed the highest average 1st-year GPA (Indian = 2.96, Viet = 2.95) and retention rates (Indian = 88.4%, Viet = 87.5%) among freshman APIDA, above both the university and APIDA averages. However, Indian and Viet transfers showed relatively lower average 1st-year GPAs (Indian = 2.74, Viet = 2.86) and retention rates (Indian = 83.5%, Viet = 85.5%) among transfer APIDA students, below both the university and APIDA averages. These findings (see Figures 3 and 4) again highlight the diverse academic trajectories in the APIDA student population, emphasizing the need to explore within-region variations and how differences might exist for a specific detailed ethnicity group (e.g., Indian), depending on whether they are first-time freshmen or new transfer students.

Figure 3. Average 1st-year GPA of New Asian Pacific Islander Desi American Undergraduates, 2009–2021



Note: EA = East Asian, FIL = Filipino, NHPI = Native Hawaiian and Pacific Islander, SA = South Asian/Desi, SEA1 = Southeast Asian 1: Refugee, SEA2 = Southeast Asian 2: Geography.

Figure 4. Retention Rates of New Asian Pacific Islander Desi American Undergraduates, 2009–2021



Note: EA = East Asian, FIL = Filipino, NHPI = Native Hawaiian and Pacific Islander, SA = South Asian/Desi, SEA1 = Southeast Asian 1: Refugee, SEA2 = Southeast Asian 2: Geography.

Case Study Summary

We used a funnel-shaped disaggregation framework to analyze the APIDA undergraduate population at our university, regrouping detailed ethnicities into regional groups informed by immigration histories. This framework allowed for between-region and within-region APIDA group comparisons. Our exploration revealed significant diversity and variation in demographic profiles and academic outcomes, emphasizing how the APIDA pan-ethnic category can obscure disparities within the community. Notable findings include variations across APIDA regional groups (e.g., Southeast Asian 1: Refugees are the most likely to be first-generation and Pell-eligible), within-region differences (e.g., Korean freshman students have lower 1st-year GPA and 2nd-year retention rates than other East Asian groups), and potential moderations by student entry type (e.g., Indian transfer students have 1st-year GPAs below the university average for transfers, whereas Indian freshmen have GPAs that exceed the university average for freshmen).

Moreover, while the complexity, privacy, and confidentiality of data disaggregation may pose challenges for widespread buy-in and implementation by institutions, our case study demonstrates that a systematic approach can be used to overcome these challenges, facilitating more intentional and equity-minded data disaggregation. First, while it is counterintuitive to data disaggregation and not always ideal, we found value in regrouping the disaggregated ethnicity or national origin groups into specific contextual categories; in this case, we regrouped by regions of Asia and the Pacific Islands informed by immigration histories. Grouping with intention allowed for more-parsimonious analyses while still retaining the nuance needed to understand disaggregated patterns. Additionally, intentional grouping can help to address challenges related to statistical power and data confidentiality posed by small group sizes resulting from disaggregation, especially at institutions with smaller numbers of minoritized student populations. Institutions pursuing this work should consider whether grouping by intention would benefit their data disaggregation. For example, the Latinx population can be regrouped into regions, such as Central America and South America, and the White population can be regrouped by ancestry, such as Western European and Eastern European.

Second, the data structure of disaggregated regional categories allows for examination between disaggregated categories (e.g., Central American students and South American students) and within disaggregated category comparisons (e.g., Honduran students and Chilean students). Rather than just comparing between pan-ethnic groups, a more useful approach could be to explore the diversity within these groups, since within-racial variations have been found to be at times more pronounced (Read et al., 2021), reflecting diverse experiences that are obscured when aggregated.

Third, our case study suggests that further breaking down disaggregated data into additional demographic variables can play a role in identifying disparities within pan-ethnic groups. This approach provides a more detailed analysis, considering additional factors or characteristics, that can help reveal nuanced variations within the broader pan-ethnic groups. For example, we compared the disaggregated data by student entry type (first-time freshmen and transfer students). Future institutional research could also differentiate the disaggregated data by demographic variables such as gender (e.g., male Hmong and female Hmong students; Teranishi & Nguyen, 2020).

Fourth, in addition to grouping with intention to strengthen data confidentiality and statistical power, we further increased group sizes and privacy by aggregating cohort data from new students entering the university between Fall 2009 and Fall 2021. We also chose to suppress (or hide) data when groups had fewer than 10 individuals. Together, these three practices helped increase data integrity and reduce the risk of data reidentification of sensitive information resulting from disaggregation in our case study.

Finally, to make sense of and present disaggregated findings, we presented our data visualization as a model. Using bar graphs for the disaggregated groupings with comparative trend lines for the aggregated and university averages can help researchers and readers quickly comprehend the trends and patterns of the disaggregated data.

In sum, our process illustrates how the risks, complexity, and possible messiness of race/ethnicity data disaggregation can be addressed and made more cohesive by intentional groupings and step-by-step comparisons. Next, building on the insights gained, we present a framework to contextualize the continuum of readiness of postsecondary institutions to do this work, and we give suggestions on how they can progress—or level up—in this work.

FRAMEWORK FOR RACE DATA DISAGGREGATION READINESS

We recognize that there is a wide range of readiness and capacity across institutions to do the work of disaggregating race/ethnicity data. In order to meet institutions where they are, we have developed a framework of Race Data Disaggregation Readiness (RDDR). We describe the five levels of RDDR below, with recommendations for doing the disaggregation work based on level of readiness. As readers attempt to classify their institution's level of readiness using this framework, we recommend that they learn more about the data being reported. If student race/ethnicity data are usually reported only in larger aggregate categories, it does not necessarily mean that additional detailed information is not available. It is therefore critical that the source of these data is identified to fully understand what types of data are available.

Level 1: No Further Disaggregated Race/Ethnicity Data

Although most colleges and universities participate in IPEDS reporting, they are only required to collect data on the larger race/ethnicity categories (National Center for Education Statistics, n.d.). In other words, many institutions will have no further detailed race/ethnicity data beyond what is required for federal reporting.

For these Level 1 institutions, it will be vital to make the case for the added value and critical importance of having the additional disaggregated data. It will be difficult to make that case without having the data on hand, so the best way to do so might be by collecting these data oneself, perhaps in a voluntary student survey (see Kodama [2021] for a case example). Even if these data represent only a fraction of the student body, collecting them will at least allow for some data-informed arguments in support of the value of further disaggregated race data. For example, the data may reveal that one particular national origin group within a pan-ethnic race group has particularly low academic outcomes and that averaging this group with all the other subgroups within that pan-ethnic group results in obscuring their poorer outcomes. Researchers may choose to target specific racial/ethnic groups in such data collections when they have intimate knowledge of the student body and surrounding communities at the particular institution (e.g., institutions in Michigan, the state with the largest Arab American population in the nation, may decide to collect disaggregated data on this group to begin their efforts).

Level 2: Some Further Disaggregated Race/Ethnicity Data, but Limited

Some institutions collect additional detailed race/ethnicity data, but in a very limited capacity (e.g., what they assume to be the largest national origin groups, plus other). In order to both better represent the wide range of backgrounds within each race category, as well as to track changing demographics, it is essential that institutions develop more options that are comprehensive.

For these Level 2 institutions, like Level 1 institutions, much of the work will be in convincing institutional stakeholders of the critical importance of having these additional data. Concerned stakeholders at these institutions may have to gather additional disaggregated data themselves, as mentioned above for Level 1 institutions. It is also critical to gain access to whatever disaggregated data exist to better understand how comprehensive they are and what holes might exist in those data. These data can also serve as an opening to conversations about the value added in the existing disaggregated data and what further value could be gained by expanding on these categories. For example, if data are collected on only two or three subgroups within a major racial/ethnic category and these subgroups show different patterns of enrollment or outcomes, those collections can open the door to curiosity about other subgroups that are not represented, which can help to motivate the case for collecting additional disaggregated data.

Level 3: Further Disaggregated Race/Ethnicity Data Exist, but Are Not Analyzed

Just because disaggregated data are available does not mean they have been examined or analyzed. In fact, in some cases only a few individuals at these institutions might even know that such disaggregated data are available. For this reason, it is important that stakeholders interrogate the source of these data to better understand what data are available, even if they are not analyzed or widely reported.

It will be essential for Level 3 institutions to convince stakeholders of the utility of analyzing disaggregated data. We recognize the catch-22 of this situation: it is difficult to make the case for what is revealed by these sorts of analyses when the analyses have not been done. As institutional research/institutional effectiveness (IR/IE) professionals, these analyses are a crucial way that we can contribute to diversity, equity, inclusion, and justice efforts on our campuses. For those whose IR/IE offices are either not motivated to do this work or who lack the capacity to do so, it might be helpful to lean into other concerned stakeholders, including the data owners, who can additionally guide and motivate the direction of this work. For example, on a campus in which enrollment of a particular racial/ethnic group has been declining, a better understanding of the disaggregated data could improve recruitment and yield efforts; these motivations could lead to grants or other sources of funding that could help with building capacity for these types of data collections and analyses.

Level 4: Analyses of Further Disaggregated Race/Ethnicity Data Have Been Conducted

For those institutions that have disaggregated race data and have conducted analyses to better understand these data, we encourage IR/IE professionals and other stakeholders to think through how the data story is developed and disseminated on their campuses. In other words, the work does not end with the analyses; rather, that is when the sense making and advocacy begins.

These Level 4 institutions will need to consider the challenges and strengths that are evident in the data to develop their data story and how it will be disseminated to key stakeholders. As we have demonstrated with our case study, this kind of disaggregated data can result in an overwhelming array of findings. It is therefore essential that IR/IE professionals and others who have worked on the data analyses tell a clear and compelling data story. Our case study with the APIDA data demonstrates that subgroupings—such as the regional groupings we used—can be useful for summarizing findings with disaggregated data. At the same time, these subgroupings could result in the same kinds of issues as the larger racial/ethnic group summaries in terms of obscuring the outcomes for specific groups. As the data story is developed, Level 4 institutions will need to consider how to balance the additional nuances and details provided by further disaggregation of race data with the need to tell a coherent data story.

Level 5: Analyses of Further Disaggregated Race/Ethnicity Data Have Led to Development of Action Plans

Ultimately, in this work, we are striving toward not just collecting, analyzing, and disseminating further disaggregated race data, but also using these findings to motivate action on our campuses. As IR/IE professionals, one of our key roles is to help campus stakeholders to make data-motivated decisions, and these data can help to ensure that data-motivated decisions move our campuses toward greater diversity, equity, inclusion, and justice.

It is our hope that any Level 5 institution is celebrating these achievements on campus. At the same time, it is important to keep in mind that action plans take concerted effort to become a reality, and we need to continue to engage in formative evaluation of outcomes to ensure that we are achieving the results we hope for.

RACE DATA DISAGGREGATION READINESS EXAMPLES

To provide more-concrete examples of institutions on different ends of the RDDR spectrum, we provide two institutional examples: (1) Oakton College, a Level 1 institution in Illinois, and (2) CSUN, a Level 4 institution in California.

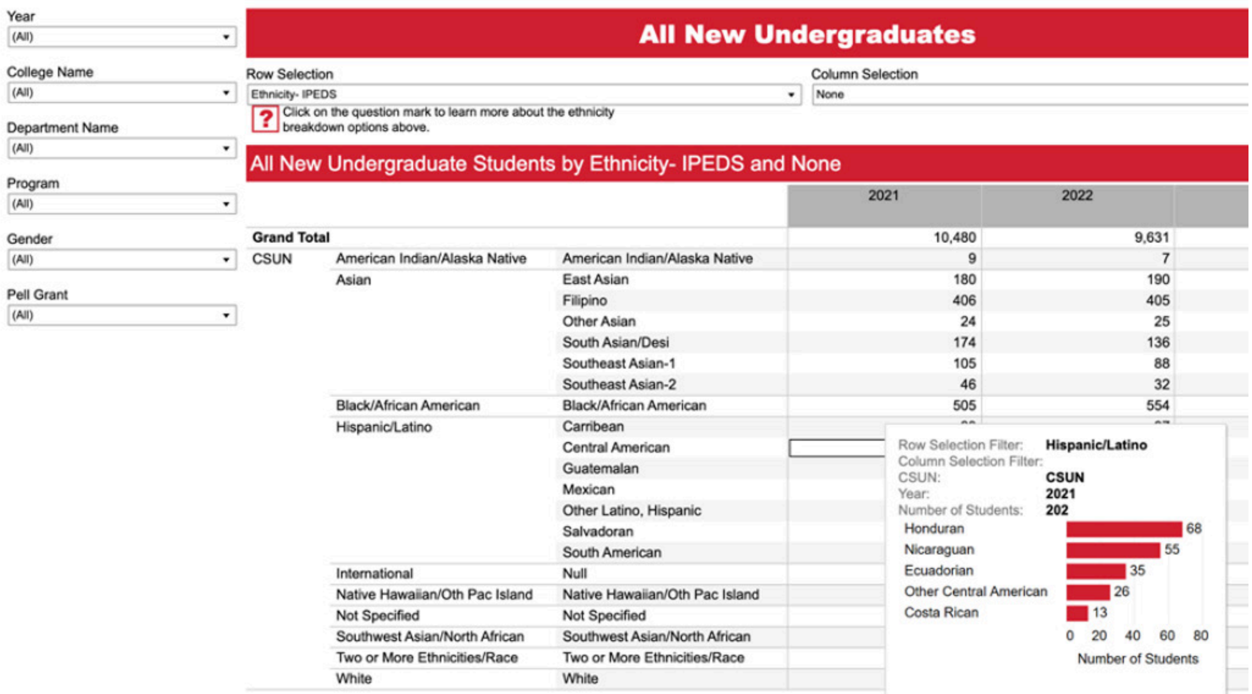
OAKTON COLLEGE

With their institution's first-ever Asian American and Native American Pacific Islander–Serving Institutions grant, Oakton College established its Center for Organizing Minority Programs to Advance Student Success (COMPASS; oakton.edu/life-at-oakton/diversity-at-oakton/aanapisi.php). One of the aims of COMPASS is to highlight the importance of disaggregated data on APIDA students. The college had never collected disaggregated data on this population, but COMPASS now sends a voluntary survey to all new APIDA students to gather these data, and the center is using the findings from this survey to work with their colleagues in enrollment and IT to further institutionalize these data. COMPASS is creating a systematic way to collect data from all students when they register for classes and to make it part of their student record. Having these sorts of disaggregated data, although not yet for all students, has helped the center to better advocate for their APIDA students and to more clearly demonstrate student needs.

CALIFORNIA STATE UNIVERSITY, NORTHRIDGE

Our institution is an example of a Level 4 institution. As we have demonstrated in the case study of our APIDA data, we have engaged with in-depth analyses. We have also conducted similar analyses of our Latinx and Black student populations. We are now thinking through how we share this data story in a way that is coherent while also capturing all the rich variations evident in the data. One way that we are doing this in our data visualizations is by showing the regional subgroupings in our institutional dashboards, but also offering a deeper dive into the national origin groups' data with a visualization within visualization option (available in Tableau, the business intelligence platform used by our campus; see Figure 5). On the face of it, the dashboard shows visualizations and data for the regional groupings, but when users hover a cursor over data points, another visualization appears that shows the data for the national origin groups within the regional group in question. In this way, we aim to provide these disaggregated data in a way that is not overwhelming to the user, but that also allows them to explore the disaggregated data further.

Figure 5. California State University, Northridge Counts Disaggregated Visualization within Visualization Dashboard



Limitations and Considerations

While our case study and RDDR framework make significant contributions to race data disaggregation research and practices, several limitations and considerations should be noted. First, beyond descriptive statistics comparisons, no further statistical analyses were conducted to test the significance of the observed differences found in the disaggregated data. Therefore, we are unable to draw definitive conclusions about the differences themselves or to identify potential factors driving them, such as first-generation student status, Pell eligibility, or student major. Within the scope of this article, however, our findings contribute to the field by demonstrating that there are, in fact, potential differences among ethnic and national origin groups when they are disaggregated from their pan-ethnic groupings. As such, these initial insights point to race data disaggregation as an important area of consideration for future inquiry. Future research can further investigate and test such differences. Additionally, guidelines and practices will need to be developed to address the statistical power in significance testing when disaggregated group sizes are too small.

Second, although aggregating cohort year data yielded larger group sizes for our comparisons (especially for ethnic or national origin groups that were too small otherwise) and safeguarded against data reidentification, this decision assumes stability in the groups across time. If some of the groups are not stable across time (e.g., the demographic profile of Bangladeshi students between cohorts 2009 to 2021), it could bias the data and misrepresent the overall comparisons between the disaggregated groups. At least for demographics, however, research suggests high income immobility across time among racial/ethnic groups, especially at the within-group level for Asian Americans (Akee et al., 2019). Future research could incorporate stability testing in their analytic plan, such as through time-series visualizations, as an assumption that needs to be satisfied when aggregating across cohort years for data disaggregation. Furthermore, narrowing the period can help account for changes in trends (albeit doing so loses statistical power due to smaller group sizes). Finally, aggregating across cohorts might not allow researchers to detect changes in academic outcomes over time (i.e., reaching parity or widening inequality). Therefore, the decision to aggregate cohort years could ultimately depend on the research question of interest.

Third, while our regional groupings informed by immigration histories helped us make sense and better manage the disaggregated data, our findings evidenced notable within-regional ethnic group differences (e.g., Korean freshman students having lower 1st-year GPA and 2nd-year retention rates compared to other East Asian ethnic groups). This highlights the need to continually assess and modify regional groupings to capture the diversity and account for contextual factors that may influence the within-regional ethnic group differences (e.g., Korean American students in the Southwest might differ from Korean American students in other geographical areas in the United States). Furthermore, while Viet, Hmong, Khmer, and Lao individuals are often grouped together due to being refugees of wars and political instability, researchers could consider including the Burmese population in this grouping because many are also refugees. Therefore, researchers should also disaggregate to detailed ethnicity and national origin groups whenever possible, and continue to refine and modify conceptualized regional groupings.

Fourth, while our university is rich in diversity, other institutions might have a much smaller population of students from minoritized racial/ethnic backgrounds. Thus, while being an informative reference point, these institutions may not be able to engage as fully with the practices presented in our case study and the suggestions put forward by the RDDR framework. Finally, as affiliates of our university's institutional research office, we had access to the collected disaggregated race data. Researchers interested in race disaggregation without such direct connections could be disincentivized to engage in the work despite potential expertise in student populations. IR/IE offices engaging in race data disaggregation should create pathways for collaboration and access to the data for interested stakeholders.

DISCUSSION

In order to serve students well, it is necessary to truly understand who our students are and what unique struggles they face in attaining their higher education goals (Hurtado et al., 2012). Many institutions still fall short of understanding the true diversity of their student bodies; the experiences of some of the most vulnerable student populations are rendered invisible because of the inability to tease apart institutional data beyond broad racial/ethnic categories (e.g., APIDA, Black, Latinx), into more-detailed subgroups (e.g., Hmong, Haitian, Salvadoran). Therefore, to ensure students of minoritized racial/ethnic groups are seen and represented, higher education institutions must systematically and intentionally disaggregate race data.

Our case study disaggregating an APIDA undergraduate population offers a detailed account of our procedure to serve as a roadmap for institutions seeking to disaggregate race data. We found that the APIDA aggregate grossly misrepresented many regional and ethnic subgroups. Specifically, we found significant diversity and variation in demographic profiles and academic outcomes across APIDA regional groups (e.g., Native Hawaiian freshman students exhibiting the lowest 1st-year GPA), within-region differences (e.g., more than double the Pell eligibility for Bangladeshi compared to Indian students within the South Asian/Desi region), and potential moderations by student entry type (e.g., Viet transfer students with 1st-year GPAs below the university average for transfers, but Viet freshmen with GPAs that exceed the university average for freshmen). These findings highlight the importance of race disaggregation to render visible the disparities overlooked within broad racial/ethnic groups. While the complexity, privacy, and confidentiality of data disaggregation may pose challenges for widespread buy-in and implementation by institutions, our case study demonstrates that a systematic approach can be used to overcome these challenges, facilitating more intentional and equity-minded data disaggregation.

Data Confidentiality

For IR/IE professionals, engaging in race data disaggregation requires striking a fine balance between subsetting the pan-ethnic data into more-granular ethnicity groups and protecting student confidentiality. We advise institutions to follow their campus's general practices and policies around handling data reidentification risk and to take into account whether disaggregated information shared in dashboards or reports will be public facing or private for internal or stakeholder purposes. For any public-facing dissemination of disaggregated data, we recommend hiding (or suppressing) groups with fewer than 10 students. On the other hand, if the data are private facing, there might be a case to be made that the value added in sharing such data outweighs the potential costs. For instance, this could allow IR/IE professionals and interested stakeholders to point out that their university has only one or two Native Hawaiian students for recruitment and outreach implications, rather than "disappearing" them by excluding them due to small group sizes. Moreover, potential workarounds to keep data from smaller ethnic groups visible is to intentionally group them with other ethnicities that have conceptual reasons to be similar (in our case, by regions informed by immigration histories) and/or to combine data across cohort years to increase group sizes.

Regrouping with Intention

Due to the complexity of data disaggregation stemming from the diverse number of individual trends and patterns that require interpretation, we recommend intentional grouping, such as by regional groups, for more-parsimonious analyses. This approach retains the nuance needed to understand disaggregated patterns. We also suggest that pulling out specific ethnic groups to acknowledge their unique characteristics within these regional similarities warrants individual analyses, especially if the group is large enough. We present the sociopolitical and regional groupings as one approach and encourage other institutions to consider groupings that are relevant to their context.

For instance, an alternative method for determining decision-making for groupings is to build on the term *underrepresented-minority group* (URM), which combines Black, Hispanic/Latinx, and Native Americans due to their historically disadvantaged status. Extending this idea, if an institution has a large number of Indian and Viet students and smaller counts for other ethnic groups in the South Asian/Desi (e.g., Bangladeshi, Nepalese) and Southeast Asian 1: Refugee (e.g., Khmer, Lao) categories, these smaller groups could be combined based on potential conceptual similarities in demographic profiles, such as first-generation status and Pell eligibility. Meanwhile, Indian and Viet students could be kept as separate distinct groups due to their larger numbers.

On the other hand, grouping national origin groups solely based on regional context, *without careful intention*, can lead to significant misrepresentations of certain groups within the aggregate. For example, the advocacy to reclassify the Hmong community from East Asian to Southeast Asian in the U.S. Census underscores the need for thoughtful regrouping (Southeast Asia Resource Action Center, 2023). Our case study highlights that Hmong students differ significantly from East Asian ethnic groups, and that they align more closely with Southeast Asian 1: Refugee groups.

In sum, if there is a conceptual justification for the groupings that help make sense of the disaggregated data, and potential limitations and drawbacks are acknowledged, there is no single perfect method to determine which groups and how many groups to use in APIDA disaggregation work. We use and recommend regional groupings further informed by immigration histories as a method of intentional grouping. This approach carefully considers the conceptual similarities between ethnic subgroups, and the shared context among the groups could play an important role in the design and implementation of potential institutional programming and resources that are culturally sensitive.

Analyzing and Presenting Disaggregated Data

We used a funnel-shaped disaggregation framework to analyze the APIDA undergraduate population at our university, regrouping detailed ethnicities into regional groups informed by immigration histories. This structure facilitated both between-regional and within-regional comparisons among CSUN's APIDA undergraduates. Rather than comparing APIDA students solely against White and other major racial/ethnic groups, this framework allowed for more-meaningful comparisons within the APIDA student population itself. This two-tiered between-region and within-region methodology enabled us to explore variations in demographics and academic outcomes across APIDA regional groups, compare them with other racial/ethnic groups, and delve into specific regional contexts. We recommend this model be used by other institutions that want to engage in race data disaggregation.

Additionally, our case study suggests that breaking down the disaggregated data to a greater extent by demographic variables (in our case, by first-time freshmen and transfer students) can play a role in further identifying disparities within pan-ethnic groups. This approach provides a more-detailed analysis, considering additional factors or characteristics, that may help reveal variations within the disaggregated groups. Future institutional research could also differentiate by demographic variables such as gender (e.g., male Samoan students and female Samoan students). Finally, to make sense of and present disaggregated findings, we presented our data visualization as a model. We recommend the use of bar graphs for the disaggregated groupings with comparative trend lines for the aggregated and university averages to help researchers and readers quickly comprehend the trends and patterns of the disaggregated data.

Building from the insights gained in our case study and recognizing the varied capacities of institutions to disaggregate race/ethnicity data, we presented our RDDR framework. This framework contextualizes this work in a continuum and provides suggestions for how postsecondary institutions could progress—or level up—in readiness based on their access to disaggregated data, analytic approach, and dissemination strategies, while also acknowledging the unique challenges administrators can encounter along the way. Without data disaggregation, minoritized student populations remain invisible to institutional leaders who need to provide focused, targeted equity programming. More postsecondary institutions should adopt and implement data disaggregation practices to inform their university programming. As highlighted in RDDR, it will be important for Level 1 and 2 institutions (no disaggregated data or limited disaggregated data) to collect and analyze disaggregated data themselves and to present findings to highlight the added value of systematic collection of disaggregated race data. For Level 3 (no analyses conducted) and Level 4 institutions (analyses conducted), the goal will be to conduct disaggregated data analyses and make sense of the granular findings to reach Level 5, in which university action plans informed by the disaggregation have been developed.

Moreover, our case study on the APIDA undergraduate student population at CSUN showcases only one broad racial/ethnic category that can benefit from data disaggregation. As such, more disaggregated work needs to be done to better understand the diversity in the Latinx, Black, Native American, Southwest Asian and North African, and White populations. For example, Latinx is another broad pan-ethnic label, representing more than 20 countries with distinct cultures and immigration histories (Lopez et al., 2023). Additionally, while many Black Americans have lived in the United States for many generations, a large proportion of this population are recent immigrants from countries in Africa and the Caribbean (Tamir, 2022).

Furthermore, when engaging in disaggregated work, it is crucial to consider the local context to enhance the sense-making process. For example, in our case study, we found that Filipino undergraduate students at our university were the least likely among APIDA ethnic groups to be first-generation and Pell recipients. This contrasts with disaggregated systemwide University of California data, which indicate that Filipino students are one of the APIDA ethnic groups most likely to be first-generation and Pell recipients (Reddy et al., 2022). As such, researchers should also be careful about how disaggregated findings can vary across local contexts.

CONCLUSION

Data disaggregation of pan-ethnic groups (e.g., APIDA, Black, Latinx) into detailed ethnicity or national origin (e.g., Hmong, Haitian, Salvadoran) reveals visible patterns of inequity that would otherwise be concealed by the aggregated pan-ethnic grouping. Therefore, to ensure that all minoritized racial/ethnic groups are seen and represented, higher education institutions must move beyond reliance solely on aggregated pan-ethnic data and systematically disaggregate the data into detailed subgroups. To help fill the critical gap in resources to inform this practice, we presented a detailed account of our procedure disaggregating our APIDA undergraduate population and recommended practical strategies. We also introduced the RDDR framework to contextualize the continuum of readiness of postsecondary institutions to do this work, and how they can progress—or level up. Only when institutions truly understand who they are serving can a diversity, equity, and inclusion–centered lens be achieved and reach its full potential. Until then, those efforts will always fall short.

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