Challenging the Model Minority Myth: A MAIHDA Study of Asian Student Outcomes in Introductory Physics

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Abstract

The model minority myth obscures the educational disparities among Asian student groups in physics education. This study estimated the variation in conceptual physics knowledge across 19 Asian racial/ethnic groups at the start and end of introductory physics courses. Utilizing data from the LASSO platform, we analyzed responses from 16,810 students enrolled in 493 introductory calculus-based physics courses across 64 U.S. institutions. We applied Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) to analyze the student outcomes with the Force Concept Inventory and Force and Motion Conceptual Evaluation. We found that the predicted *posttest* score of the lowest performing group is the same as the predicted *pretest* score of the highest performing group. Disaggregated data reveal performance differences among Asian groups that aggregated reporting conceals. To avoid the challenges that can arise when disaggregating data, instructors and researchers must consider many factors, such as research questions and/or methodological constraints. By leveraging the expanded identity options within the LASSO platform and the MAIHDA model, our approach offers a powerful framework for exposing hidden disparities and advancing equity in STEM education.

Keywords: Asian student outcomes, MAIHDA model, LASSO, disaggregating data.

Introduction

The model minority myth is a stereotype that homogenizes all Asian Americans into a monolithic group of overachievers (Wu, 2013; Museus & Kiang, 2009). This stereotype masks the distinct subgroups within this broad conglomeration and perpetuates anti-Black racism. Researchers have documented how policymakers, media, and dominant institutions weaponize the "model minority" stereotype of Asian Americans, portraying them as high-performing despite their minority status, to undermine efforts toward racial equity and to blame Black Americans for systemic disparities (Wu, 2013; Kim, 1999; Museus & Kiang, 2009; Poon et al., 2016). In educational research, the model minority myth often contributes to the aggregation of all Asian American students into a single category. Several works called for the disaggregation of the broad Asian categorization in physics and STEM fields, as this can reveal disparities masked by the model minority myth (Li & Zhao, 2025; Shafer et al., 2021; Zhang et al., 2025).

Research questions

In this article, we critique the common idea that Asian Americans are a homogenous, high-achieving group. We challenge the practice of aggregating Asian students into a single group or with White students without being aware of and transparent about the impacts of these choices on model outcomes and conclusions. Disaggregated data is necessary, though not sufficient, for developing and implementing educational policies and practices that serve all students and broaden participation in physics and STEM education.

1. To what extent does average physics conceptual knowledge vary across Asian ethnicities at the start and end of introductory college calculus-based physics courses?

Positionality

Author 1. I identify as an Asian cisgender woman, raised in rural southeast Vietnam. My educational and professional path, from earning a physics degree in Vietnam to pursuing graduate studies in education in the U.S., has spanned transnational and intersectional contexts. I began teaching high school physics in Vietnam and later taught college-level physics in the U.S., working closely with Asian Indian students. Cross-cultural experiences among different races have enhanced my understanding of educational systems and the varied experiences of learners. I advocate for creating inclusive learning environments where students from all backgrounds feel respected, supported, and empowered to succeed.

Author 2. I identify as a White, cisgender woman, and recognize that this, along with my limited physics background, shapes the perspective I bring to the paper. I graduated with a bachelor's degree in psychology and am currently pursuing a master's degree in teaching, where I hope to work with students from rural, low socioeconomic backgrounds similar to the one I grew up in. In my classroom, I hope to practice culturally responsive teaching and center on forging positive relationships between myself and my students. The work I have done with foster youth has informed my awareness of how systemic barriers and limited support can impact educational outcomes and attainment. I am passionate about students recognizing the value and importance of their unique voices and perspectives, and the strengths they bring to academic spaces.

Author 3. As a White man, I recognize that I benefit from systems of privilege and power that shape opportunities in American society, including in science and education. My motivation to pursue this work also comes from my own experiences of how science has been empowering and liberating in my life, and from my desire to make those opportunities more widely accessible. I seek collaborations and projects that push forward my own growth while advancing collective efforts to support students who are marginalized by racism, sexism, classism and other systems of oppression to pursue their goals and curiosity. This study fits within my work using disaggregated data and intersectional research methods to better measure student outcomes and to inform policies and practices that expand participation and success in STEM.

Author 4. I identify as a White cisgender man. I earned a bachelor's degree in physics, have engaged in physics research, was a high school physics teacher, and now have a Ph.D. in education and prepare future science teachers. Raised in low-income households, I now earn an upper-middle-class income. Throughout my career, I have actively engaged with diverse educational contexts, including hosting Japanese exchange students and facilitating student exchanges to Japan. This involvement has afforded me an appreciation of cultural and educational dynamics, particularly in East Asian contexts, though I acknowledge that these experiences do not fully bridge the gap to the lived realities of marginalized communities in the

U.S. People with similar privileges to mine have created and maintained our society's unjust power structures. As a person with privilege, I believe it is my obligation to use that privilege to dismantle oppressive systems, while also recognizing that my perspective is limited by that very privilege.

Definition

Terms	Definitions
Model Minority Myth	A stereotype that homogenizes Asian Americans as highly successful, flattening the variety of cultures, languages, and histories among different ethnic groups within this strata (S. J. Lee, 1994; Poon et al., 2016).
Critical Race Theory (CRT)	A framework originating in legal studies, created to address racial injustices and oppression. Assumes racism is embedded within institutions, and prioritizes amplifying the narratives of the oppressed (Ladson-Billings & Tate, 1995).
Asian Critical (AsianCrit) Theory	An extension of critical race theory (CRT) that centers Asian American experiences (Museus & Itikar, 2013).
Quantitative Critical Race Theory (QuantCrit)	Applies the principles of CRT to quantitative research, analyzing how data and statistical methods can reinforce racial biases and contribute to systemic oppression. Critiques the assumption of neutrality in numbers, advocating instead for using numbers to challenge racial injustices (Gillborn et al., 2018).
Intersectional identities	A term referring to how social identities, such as race, ethnicity, and gender, interact to shape individual experience. The focus of intersectionality is how these identities interact dynamically with power structures, leading to inequities (Crenshaw, 1991).
Multiple Imputation (MI)	A probabilistic method for handling missing data that preserves statistical power and reduces bias by incorporating uncertainty into the imputation process (Rubin, 1987; Woods et al., 2024).
Multilevel Analysis of Individual Heterogeneity and Discriminant Analysis (MAIHDA)	A statistical modeling method designed for intersectional research, which leverages multilevel modeling to nest individuals within social strata (Evans et al., 2024).
Social strata	Strata represent the intersections of social identities such as race, class, and gender within a set of power structures. These strata reflect interdependent and mutually constituted systems of power and inequality (Evans et al., 2024). In MAIHDA, researchers use strata to quantify outcome differences across these intersections.

Table I: Definitions of terms.

Literature review

Model Minority Myth

The model minority myth is an anti-Black stereotype that portrays Asian Americans as a monolithic group of overachievers (Poon et al., 2016). Politicians and journalists have historically used this myth to contrast Asian Americans with other marginalized groups, particularly Black Americans, to undermine demands for racial justice and reinforce claims that systemic racism can be overcome through individual effort (Kim, 1999; Museus & Kiang, 2009). Media narratives often attribute Asian American success to cultural values, such as a strong work ethic or a focus on education, overlooking the wide-ranging differences in culture, language, and immigration patterns among the more than 40 Asian ethnic groups in the United States (Krogstad & Im, 2025; S. Lee et al., 2017). This myth dismisses the challenges Asian Americans have faced and perpetuates the stereotype that all Asian Americans are successful. This excludes them from racial discourse and limits research and policy work being done to support them (Museus & Itikar, 2013).

Historical roots of the model minority myth emerged during World War II (Wallace, 2021; Wu, 2013). After China became an ally in World War II, Congress repealed the Chinese Exclusion Act, and the United States began to develop divergent narratives between groups that were once conglomerated. Chinese Americans became allies, and Chinese-born immigrants were newly permitted to become U.S. citizens. Japanese Americans, in contrast, were branded as enemies and were mass imprisoned in concentration or "relocation" camps.

Following World War II, and the 1944 release of Gunnar Myrdal's *An American Dilemma*, social scrutiny of racial relations and discrimination in the U.S. was on the rise (Wallace, 2021; Wu, 2013). Myrdal attributed the racial disparities faced by Black people in America to White prejudice rather than inherent racial differences (Myrdal & Bok, 1996). The media, eager to shift the focus of the blame, began to release articles comparing Black Americans to Asian Americans. They developed narratives portraying Asian Americans as more diligent and hardworking than Black Americans, and leveraged these narratives against Black communities. William Peterson's "Success story: Japanese American style" came out during this time, often attributed to the first articulation of the model minority myth, although the term itself is not used (Kim, 1999). In his New York Times article, Peterson argues that Japanese Americans succeeded in spite of their own disparities, using their success against Black Americans, who he refers to as "problem minorities" (Pettersen, 1966).

The 1965 Watts Riots, a protest against police violence in Black communities in California, are another example that brought the model minority myth into mainstream discourse (Iftikar & Museus, 2018). Daniel Moynihan, the Secretary of Labor, published a report contrasting the high unemployment rates of Black men with the perceived diligence of Asian American families. This reinforced the model minority myth, framing it as though Black

communities were at fault for inequalities and triangulating Asian Americans as a buffer, "better than Blacks but inferior to Whites" (Iftikar & Museus, 2018; Kim, 1999).

Poon et al. (2016) warn that disaggregated data on educational disparities are not enough to dismantle the myth. Instead, they encourage researchers to focus on accurately portraying the experiences of Asian Americans in education by working directly with these groups. They also warn against the use of broad panethnic terminology, such as "Asian American and Pacific Islander," particularly when discussing the myth, as these groups have unique histories and identities, and thus experience racialization in the United States differently (Poon et al., 2016).

Shafer et al. (2021) examined course grades in university-level physics courses and found no evidence of racial inequities when using URM and non-URM groupings. However, after disaggregating the data by specific racial/ethnic groups, Shafer et al. revealed that Black and Asian American students underperformed relative to their non-Hispanic White peers, inequities that the URM's aggregated identities had concealed.

When equities are disguised by how data is categorized, groups that could benefit from intervention do not receive it. This relates to the work of Iftikar and Museus (2018), who advocate for the use of more specific frameworks, such as AsianCrit. They suggest that frameworks like AsianCrit can help investigate how systemic racism within educational systems impacts Asian American students. Research that centers the experiences and histories of communities of color can help challenge their marginalization in institutional decision-making and foster a more equitable distribution of resources.

Historical Trends

Historically, Asian Americans have been grouped under one broad category, disguising the variety of political, economic, and educational experiences within the Asian categorization (Krogstad & Im, 2025). Poon et al. (2016) suggest that analyzing the educational data of Asian American students should be grounded in a historical context. A report compiled by AAPI Data (AAPI Data, 2022; see Table II) reveals contrasts in educational attainment and income across ethnic groups. Median household income and bachelor's degree attainment range from \$125,319 and 75% for Indian Americans to \$66,406 and 19% for Native Hawaiians and Pacific Islanders (NHPI) (AAPI Data, 2022; see Table II).

To better understand these differences, we need to consider the historical context of Asian immigration to the United States. The first wave of Indian immigration to America resulted from Britain's colonization and land tenure in India, as many Punjab farmers navigated drought and famine (Rangaswamy, 2008). Between 1903 and 1920, Punjab villagers landed first in Canada, and then migrated down the West Coast of the United States, working primarily for lumber mills and railway companies. Immigration came to a halt with the Barred Zone Act of 1917, a result of race-based hostility that pervaded Indian-immigrants' experience in America

during this time (Hess, 1974). The 1965 Immigration Reform Act saw a drastic increase in Indian immigration to the U.S. with the transition of nation-based quotas to hemisphere-based quotas. Most Indian-immigrants travelling to the U.S. were now classified as professional or skilled workers, a contrast to the Punjab villagers from the early 1900s. Today, 54% list employment as their primary reason for migrating (AAPI Data, 2022; see Table II).

Filipino immigration to the United States has been shaped largely by U.S. military occupation and the annexation of the Philippines (Gates, 1984). The first major wave of Filipino immigration to the United States came following the Philippine-American War. After the Philippines became a U.S. territory, Filipinos were classified as U.S. nationals, allowing them to immigrate to the United States freely (David & Nadal, 2013). During this time, Filipino immigration was concentrated primarily in Hawaii and the western coast of the United States, and consisted mainly of male laborers working for sugar plantations in Hawaii, farms in California, or salmon canneries in Washington and Alaska (Gallardo & Batalova, 2020; Melendy, 1974). Another shift occurred when the Philippines gained independence in 1946, and with the change in immigration legislation in 1965. This time period consisted of a broader variety of Filipino immigrants, including the wives and children of Filipino men in the U.S., military members, students, and professionals ("Immigration History," 2014). Today, half of Filipinos in the United States have a bachelor's degree or higher, and 78% list family as their primary reason for immigration (AAPI Data, 2022; see Table II).

Southeast Asian groups, such as Cambodian, Lao, Hmong, and Vietnamese Americans, have faced histories of war, displacement, and refugee resettlement. Many arrived in the U.S. as refugees following the Vietnam War, the Cambodian Genocide, and the Secret War in Laos. In April of 1975, President Ford authorized the resettlement of 130,000 refugees from Indochina, most of whom were from Vietnam, due to the imminent fall of Saigon (Bankston & Zhou, 2021; Batalova, 2023; Bon Tempo & Diner, 2022). While the initial wave of Vietnamese immigration to the United States was through refugee status, modern immigration stems primarily through family reunification (Batalova, 2023). As of 2022, 93% of Vietnamese Americans list family as their primary reason for immigration, and this group reported among the highest rates of limited English proficiency (48.9%), and the lowest rates of educational attainment, with 32% receiving a bachelor's degree or higher (AAPI Data, 2022; see Table II).

The first Native Hawaiians who migrated to the United States did so between the late 18th and early 19th centuries, brought to the Northwestern mainland by British fur traders in Hawaii (Quimby, 1972). Hawaii was first settled by Polynesians travelling from the Marquesas Islands between 400-750 CE (Hamilton, 2025; Heckathorn et al., 2025). The arrival of British Captain James Cook in 1778 marked the first European contact with Native Hawaiians. This contact, and the ensuing immigration of Protestant missionaries from New England in 1820, introduced foreign diseases to the island that had a profound impact on the population. Over time, the Native Hawaiian population became a minority in Hawaii, with laborers from other countries such as China, Japan, and the Philippines travelling to Hawaii to pursue work on the sugar plantations, which were owned primarily by immigrants from the mainland United States

and Europe. In 1893, the Western plantation owners and missionary descendents overthrew the Hawaiian government, leading to the United States' annexation of Hawaii in 1898 (Hamilton, 2025; Kauana, 2021). Annexation had lasting impacts on the culture, language, health, and homeownership of Native Hawaiians (Kauana, 2021; Pagud et al., 2022). As of 2020, only 47% of Native Hawaiians lived in Hawaii, while 53% lived in the mainland United States (Hamilton, 2025; Pagud et al., 2022). Of the Native Hawaiians migrating to the continental U.S., many cited lack of economic opportunity and affordable housing as contributing factors (Pagud et al., 2022).

Native Hawaiians are the largest groups of Pacific Islanders living in the United States today, followed by the Samoans and the Chamorro, an indigenous group from Guam and the Northern Mariana Islands (Rico et al., 2023). The first major wave of non-Hawaiian Pacific Islanders immigrated to the U.S. in the 1950s, and this group was largely made up of American Samoans and Guamanians. American Samoans became U.S. nationals after American Samoa became an official United States territory in 1900 (U.S. Department of the Interior, 2024). U.S. Naval occupation of American Samoa significantly influenced the first wave of immigration, with many Samoan military personnel immigrating to naval bases in Hawaii after the U.S. Navy withdrew from American Samoa in 1951 (Forster, 1957). The United States annexed Guam in 1898 as a result of the Spanish-American War (Hamilton, 2025). Over 50 years passed before Guamanians were granted full United States citizenship through the Guam Organic Act of 1950 (U.S. Department of the Interior, 2023). Similarly to American Samoans and Filipinos, Chamorro immigration to the mainland United States was also influenced by the U.S. Navy occupation, as well as the Korean War and Typhoon Karen (Civil Rights Digest, 1976). Today, the average median salary of NHPI is \$66,406, and these groups experience the lowest level of educational attainment, with 19% earning a bachelor's degree or higher (AAPI Data, 2022; see Table II).

Immigration patterns vary within East Asian communities as well. Chinese immigration to the United States began in the 1850s and was concentrated primarily in the West. Chinese immigration during this time consisted mainly of male laborers, mining for gold, working in agriculture, or working for railroad companies (*Chinese Immigrants*, n.d.). Other American laborers working these positions began to blame Chinese immigrants, who had less bargaining power for the wages they were willing to accept, for bringing down the cost of labor (U.S. Foreign Relations - Office of the Historian, n.d.). This contributed to the developing resentment and hostility towards Chinese laborers, which ultimately led to the passing of the Chinese Exclusion Act in 1882. This policy heavily restricted Chinese immigration until World War II, which saw its repeal. In comparison to the first waves of Chinese immigration to the United States, immigration following the 1965 Immigration Reform Act consisted of a professional, highly skilled class, including students and businessmen (Batalova & Greene, 2025). Today, Chinese Americans have a median household income of \$84,215, with 56% holding a bachelor's degree or higher and 43.2% reporting limited English proficiency (AAPI Data, 2022; see Table II).

Korean immigration to the United States began in the early 1900s and saw its increase following both World War II and the Korean War (Yoon I-j, 1997). The first major wave of Korean

immigration to the United States began in 1903, with many Koreans immigrating to Hawaii to work on sugar plantations (Shin, 2024). The next wave of immigration followed the Korean War and consisted primarily of the wives of U.S troops in South Korea, children orphaned by the war and adopted by American families, and a professional class that included students and businessmen (Chung, n.d.). Korean immigration to the U.S. increased further in 1965, with the shift to a quota-based immigration system. This final wave of immigration was the largest, and prioritized skilled professionals and family reunification (Shin, 2024). This wave included immigrants from white-collar backgrounds from a variety of occupations that were moving to the United States by choice, seeking economic opportunity (Korean American Foundation - Greater Washington, n.d.). Korean Americans now report a median household income of \$74,958 and high levels of educational attainment, with 59% holding a bachelor's degree or higher (AAPI Data, 2022; see Table II).

Similarly to Korean and Filipino immigration, Japanese immigration to the United States started at sugar plantations in Hawaii (Stanford Medicine, 2014). The first Japanese immigrants arrived in Hawaii, and then on the West Coast of the mainland United States, particularly in California. The Meiji Restoration in 1868 and rapid move towards industrialization created political and economic unrest in Japan that acted as a push factor for many Japanese immigrants (Library of Congress, n.d.). Most of the Japanese immigrants arriving at this time were young men seeking economic mobility, as students, male laborers, or both (Akiba, 2006). The Chinese Exclusion Act of 1882 led to a high demand for labor in positions such as agriculture and railways that Japanese immigrants began to fill (Minidoka National Historic Site, 2019). They inherited the racial resentment and hostility that White Americans had developed against Chinese immigrants as a result. Between 1908 and 1924, the next wave of Japanese immigration began. Japanese women began immigrating to the United States as "picture brides" of Japanese American men, a result of a loophole in the Gentleman's Agreement, which limited the immigration of Japanese men, but allowed the wives of immigrants already in the United States to join them (Akiba, 2006). It was very difficult for Japanese American men to start a family, as many could not afford to return home to search for a wife, and interracial marriage between Japanese men and White women was forbidden by law. Picture brides resulted, which were arranged marriages between Japanese American men and Japanese women, where the prospective couple would be introduced to each other via photographs. Following World War II, another nearly 45,000 Japanese women immigrated to the United States as war brides of U.S. military men. After 1965, Japanese immigration to the United States prioritized family reunification and skilled labor, though decreasing drastically in number compared to Japanese immigration between 1900 and 1920 (Karthick, 2015). Today, the median household income for Japanese Americans is \$84,861, with 52% receiving a bachelor's degree or higher (AAPI Data, 2022; see Table II).

0	Median	Bachelor's	Limited	Immigratio	n Reasons
Group	Household Income	or Higher (%)	English Proficiency (%)	Employment	Family
Asian Indian	\$125,319	75%	18.2%	54%	43%

Filipino	\$97,816	50%	20.5%	20%	78%
Asian (Overall)	\$91,828	55%	31.9%	1	_
Japanese	\$84,861	52%	22.4%	46%	51%
Chinese	\$84,215	56%	43.2%	34%	54%
Korean	\$74,958	59%	38.8%	66%	34%
Vietnamese	\$71,014	32%	48.9%	6%	93%
NHPI	\$66,406	19%	12.2%	1	_
Other Asian	\$65,793	46%	27.7%	_	_

Table II. This table was compiled using data from AAPI's "State of Asian Americans, Native Hawaiians, and Pacific Islanders in the United States" Report from June of 2022 (AAPI Data, 2022). Note: Native Hawaiians and Pacific Islanders (NHPI).

As Table II illustrates, Asian American and Pacific Islander groups differ in socioeconomic and educational outcomes. While Indian Americans report the highest median household income and bachelor's degree attainment, NHPI reports the lowest levels of educational attainment and earnings. Vietnamese Americans also report relatively low levels of educational attainment alongside high rates of limited English proficiency. These disparities demonstrate the heterogeneity across Asian American and Pacific Islander subgroups and highlight the limitations of treating "Asian" as a monolithic category, as the model minority stereotype suggests.

The disparities reinforce calls within STEM education research for disaggregating Asian American experiences. For example, Zhang et al. (2025) challenge the assumption that Asian Americans students are overrepresented in STEM fields. During interviews, students revealed that multiple aspects of their identity impacted their identity formation in physics. Their findings suggested that intersections regarding gender, socioeconomic background, and national origin may make the representation of Asian Americans in STEM more complex. These multiple, intersecting identities are often disguised by the broader model minority stereotype.

Conceptual Framework

Asian Critical (AsianCrit) theory

In this study, we draw on AsianCrit to frame our understanding of how race and power intersect in the experiences of Asian students in physics education. AsianCrit builds on Critical Race Theory (CRT) by addressing the distinct racialization processes and sociohistorical positioning of Asian communities in the United States. While Museus and Itikar (2013) outlined seven tenets of AsianCrit, our analysis centers on three that are most relevant to our study:

- Asianization recognizes how dominant U.S. society imposes homogenous and stereotypical identities onto Asian communities, flattening their cultural and ethnic differences. For instance, Asian students are often labeled as the "model minority," a stereotype that can obscure academic challenges and discourage them from seeking support.
- Strategic (anti)essentialism emphasizes recognizing both shared and divergent
 experiences among Asian subgroups, resisting the notion of a monolithic Asian identity.
 Disaggregated educational data, for example, can highlight disparities between
 Southeast Asian and East Asian students, informing more targeted and equitable
 interventions.
- 3. Intersectionality identifies how intersections between social identities, such as race, gender, class, and language, shape complex educational experiences. In this paper, we focused on the intersection of different racialized identities within the Asian community (e.g., White-Asian, etc.). For example, Asian Indian and Chinese American groups, who report among the highest rates of bachelor's degree attainment, may also draw upon insider knowledge and social capital that facilitate persistence in STEM fields, resources that institutions restrict for other minoritized groups (Seymour & Hewitt, 1997).

Quantitative Critical Race Theory (QuantCrit)

Gillborn et al. (2018) describe QuantCrit as a critical response to address racism and biases embedded in quantitative research methods. Quantitative methods in fields such as education and psychology were influenced by the eugenics movement, which promoted racial hierarchies and White supremacy (Castillo & Strunk, 2024). QuantCrit combines Critical Race Theory with quantitative methods to challenge these oppressive histories and address current inequalities (Gillborn et al., 2018).

QuantCrit also questions the common belief that quantitative research is objective and neutral, instead recognizing that all data and methods contain inherent biases. The goal of QuantCrit is to use a racial equity perspective to critically evaluate quantitative research and promote fairness and social justice in education (Nissen et al., 2022). Our work focuses on two tenets that align with our research question, based on the definition in (Castillo & Strunk, 2024):

- Numbers are Not Neutral. QuantCrit asserts that numbers and quantitative methods are
 not neutral because they reflect human choices influenced by societal biases and
 dominant cultural norms. Our study critically examines conventional racial groupings in
 education to highlight hidden inequities masked by numerical aggregation by using
 multilevel analysis of individual heterogeneity and discriminatory precision (MAIHDA).
- 2. Categories are Neither Natural Nor Inherent: QuantCrit recognizes racial categories as socially constructed and context-dependent. In this study, we examine disaggregated data on Asian identities (e.g., Chinese, Korean, and Filipino) to reveal differences that aggregated categories (e.g., URM and non-URM) often obscure.

Methods

Data collection and cleaning

We used the data from the LASSO platform (Van Dusen, 2018), an online assessment system that supports the administration, scoring, and analysis of research-based assessments (RBAs). LASSO collects students' demographic information anonymously with their consent. The dataset contains social identity information (i.e., races, ethnicities) and their performances (i.e., student test scores) from Fall 2015 to Fall 2023. Until the end of 2019 (see Table VI in the Appendix), the LASSO platform provided racial/ethnic identity options, including "Asian", without disaggregating into more specific subgroups. Any additional Asian subgroups reported during this period came from students who selected the "Other" option and wrote in their identity. Beginning in Spring 2020, the platform offered more specific Asian identity options such as Asian Indian, Chinese, Filipino, Korean, Vietnamese, or other Asian identities. Therefore, in our analysis, the "Asian" category prior to Spring 2020 represents a broad panethnic group encompassing students from diverse cultural, national, and linguistic backgrounds. We include it in the analysis to illustrate the differences in outcomes across Asian groups that aggregation can hide.

The dataset has 16,810 students collected from 493 calculus-based physics courses across 64 institutions. We selected data from two common physics RBAs: (1) Force Concept Inventory - FCI (Hestenes et al., 1992) with 10,723 students; and (2) Force and Motion Conceptual Evaluation - FMCE (Thornton & Sokoloff, 1998) with 6,087 students (see Table III). Instructors often use the FCI (30 items) and FMCE (47 items) to assess students' knowledge of Newtonian mechanics.

	N	Pretest (%)	Posttest (%)	Pre and Posttest (%)
FCI	10,723	8,591 (80%)	7,555 (70%)	5,423 (51%)

FMCE	6,087	4,888 (80%)	3,963 (65%)	2,764 (45%)
Overall	16,810	13,479 (80%)	11,518 (69%)	8,187 (49%)

Table III. Number and percentage of student responses for the FCI and FMCE assessments. The N column represents the number of students who completed at least 1 administration (preor post). The other columns indicate the number of students who completed the pretest, posttest, or both, along with the percentage relative to the total enrolled.

We filtered the dataset to include only responses from calculus-based courses that administered the FCI or FMCE assessments. We then removed the pretest or posttest score if the student took less than 5 minutes on the assessment or answered less than 80% of the test items. For the students who provided a pretest, a posttest, or both, 20% were missing the pretest, and 31% were missing the posttest.

To handle missing data, we applied multiple imputation (MI), which reduces bias and preserves sample size. The MI approach maintained the hierarchical dependencies while imputing missing values. We set up an MI model with a three-level hierarchical structure: assessment in student, student in course, and course in institution. In R, we used the mice package (Buuren & Groothuis-Oudshoorn, 2011) to perform ten imputations with five iterations.

Data analysis

In our analysis, we identified unique social groups based on race information from the LASSO survey. Among 366 distinct social identity groups, 144 were Asian (i.e., monoracial and multiracial identities). From these 144 groups, we selected 19 that each had at least 10 student responses in pre- or posttest. The selected groups include eight monoracial identities (e.g., Asian Indian, an Asian Race Not Listed (ARNL), and Chinese), and ten biracial identities (e.g., Asian Hispanic/Latino, Chinese Vietnamese, NHPI Hispanic/Latino, and White Asian) (see Table VII in the Appendix).

In educational research, Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) (Evans et al., 2024) is a statistical approach used to analyze group-level characteristics (e.g., students, social identity groups, courses, schools, or classrooms) to explain individual educational outcomes, such as academic performance (Evans et al., 2024; Van Dusen et al., 2024). Unlike some quantitative intersectional models, MAIHDA does not employ multiple interaction terms to capture intersecting social identities (e.g., ethnicity, gender, socioeconomic status). Instead, it nests individuals within intersectional identity groups. By introducing a group-level error term, MAIHDA captures the unique outcomes for each identity combination, simplifying model complexity while addressing intersectionality (Evans et al., 2024). MAIHDA then adds this strata-level error term to the fixed effects when

predicting a social strata's outcome. We identified the social strata based on the students' race and ethnicity (see Figure 1A).

To improve model predictions and better represent social identity interactions, we used effect coding (0.5 for present, -0.5 for absent) for racial indicator variables (Mayhew & Simonoff, 2015). We included terms for whether students were retaking the class, which assessment they took, and 11 primary racial groups: ARNL, Asian, Asian Indian, Chinese, Filipino, Hispanic/Latino, Japanese, Korean, NHPI, Vietnamese, and White.

We implemented the Bayesian MAIHDA model using the brms package (Bürkner, 2017), leveraging multiple imputed datasets for a comprehensive analysis. The MAIHDA model has a three-level cross-classified multi-level model nesting tests (level 1), students (level 2), courses (level 3a) and strata (level 3b) (see Figure 1B). The model was executed using the <code>brm_multiple</code> function (Bürkner, 2017) with 2000 total iterations, with 1000 warm-up iterations to ensure accurate posterior estimation. We then combined the fixed effects and random effects from the MAIHDA model to predict each social strata's outcomes.

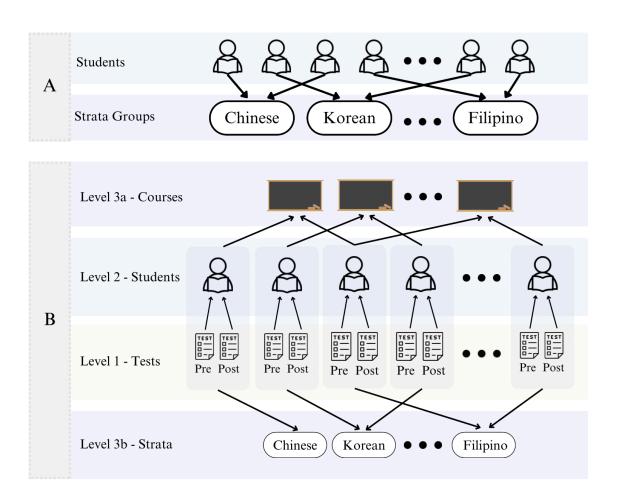


Figure 1. The MAIHDA model. Figure A illustrates how students are nested within racial/ethnic strata (e.g., Chinese, Korean, Filipino). Figure B depicts the cross-classified three-level model: Level 1 contains pre- and posttest scores, Level 2 nests students, and Level 3 cross-classifies students by course enrollment (3a) and racial/ethnic strata (3b).

Interpreting results

In this work, we report sample sizes, predicted group means, and standard errors (SEs) to support transparent interpretation of results, rather than relying on p-values. Relying on p-values risks misrepresenting educational inequities, particularly when marginalized groups are underrepresented and have smaller sample sizes, which can inflate uncertainty and obscure meaningful differences (Greenland et al., 2016; Nissen et al., 2021; Wasserstein et al., 2019). We used the degree of overlap between compatibility intervals to inform our confidence in group differences, without applying rigid thresholds. Non-overlapping compatibility intervals suggest a high degree of confidence in observed differences, while overlapping compatibility intervals indicate greater uncertainty, though overlap is not taken as evidence of no difference.

Findings

Table IV reports the predicted means and corresponding standard errors for each group. Figure 2 visualizes these results, using error bars to illustrate the uncertainty (±1 standard error) in the measurements. We do not directly examine the model's coefficients because, although the model contains many coefficients, only the 53 coefficients shown in Table VIII are used to predict a group's score (e.g., White Japanese posttest scores), and these coefficients are not meaningful without considering the context of the other terms.

Predicted mean score

Croun	NI	Pretest		Posttest	
Group	N	Predicted mean	SE	Predicted mean	SE
White Korean	20	53.5	3.2	72.1	4.0
White Asian	19	51.1	3.1	69.0	3.7
White ARNL	15	50.1	3.4	69.1	3.7
White Chinese	39	49.8	2.8	69.3	3.6
White Asian Indian	21	48.7	2.9	66.2	4.3
Korean	91	48.5	2.3	66.2	3.5
White Japanese	35	45.6	3.2	64.7	3.3
Chinese	245	44.9	2.1	62.6	3.2
Chinese Vietnamese	13	44.6	3.4	63.4	4.6
White Filipino	54	44.4	2.7	62.1	3.4
Asian Indian	259	43.1	2.2	58.7	3.5
Asian	1134	43.0	1.4	61.4	3.0

ARNL	134	41.6	2.2	56.8	3.4
Asian Hispanic/Latino	20	41.5	2.8	59.1	3.8
Vietnamese	153	41.4	2.0	60.7	3.3
Japanese	16	38.4	3.5	55.3	4.9
Filipino	82	38.2	2.2	56.3	3.5
NHPI	68	36.9	2.6	55.4	3.4
NHPI Hispanic/Latino	14	33.5	3.1	52.5	4.2

Table IV: The statistical results of predicted mean in percentage points across Asian social identity groups with pre- and posttest, including the number of student responses (N), predicted mean (M), and standard errors (SE) for individual groups. Note: white color represents the monoracial groups, blue color represents the biracial groups, and green color represents the benchmark.

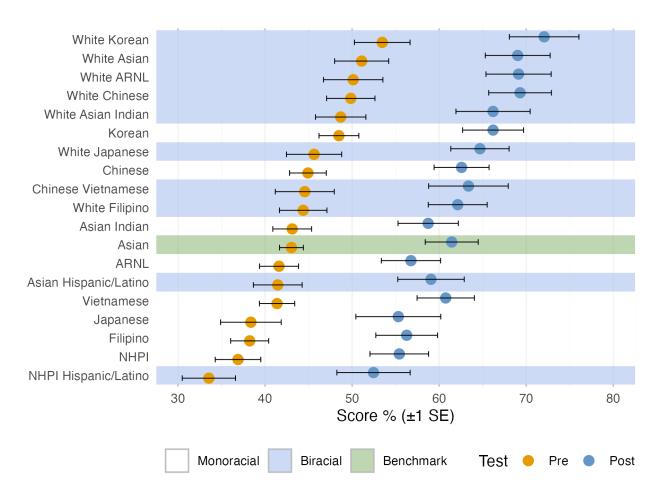


Figure 2. The predicted group outcomes with one standard error bars across 19 Asian identity groups, which varied across a 20.0% point range for pretest, [33.5 - 53.5], and 19.6% points for posttest [52.5 - 72.1]. The scores for students from the Asian group come from data collected when the LASSO platform provided fewer race options on its demographic survey, with no

finer-grained options for Asian ethnicities. Note: Asian race not listed (ARNL); Native Hawaiian or Pacific Islander (NHPI).

Pretest outcomes

For the pretest, the predicted mean for Asian students fell near the middle of the range, 43.0% points, with the smallest standard error of any group, 1.4% points. The small standard error follows from the much larger sample size due to the constrained choices students faced in identifying their race. We found that scores varied between groups, ranging from a low for Native Hawaiian/Pacific Islanders (NHPI) Hispanic or Latino (Hispanic/Latino) (predicted mean (M) = 33.5, SE = 3.1) students to a high for White Korean (M = 53.5, SE = 3.2) students, marking a total span of 20% points.

Compared to the baseline "Asian" group, six groups scored higher with non-overlapping 68% compatibility intervals: White Korean, White Asian, White ARNL, White Chinese, White Asian Indian, and Korean. Three groups scored lower than Asian with non-overlapping compatibility intervals: Filipino, NHPI, and NHPI Hispanic/Latino. The remaining groups had overlapping compatibility intervals with the baseline. Five groups had higher mean scores, including White Japanese, Chinese, Chinese Vietnamese, White Filipino, and Asian Indian. Four groups showed lower means, such as ARNL, Asian Hispanic/Latino, Vietnamese, and Japanese (see Table IV).

Posttest outcomes

For the posttest, the predicted mean for Asian students was still near the middle of the range, 61.4% points, with the smallest standard error of any group, 3.0% points. The predicted mean still ranged for NHPI Hispanic/Latino (M = 52.5, SE = 4.2) students to the White Korean (M = 72.1, SE = 4.0) students, marking a total span of approximately 19.6% points.

Compared to the baseline "Asian" student, four groups scored higher with non-overlapping 68% compatibility intervals: White Korean, White Chinese, White ARNL, and White Asian. Only NHPI Hispanic/Latino students have lower predicted scores than Asian students with non-overlapping compatibility intervals. Six groups had higher mean scores, including Korean, White Asian, White Japanese, Chinese Vietnamese, Chinese, and White Filipino. Seven groups showed lower means, such as Vietnamese, Asian Hispanic/Latino, Asian Indian, ARNL, Filipino, NHPI, and Japanese.

Learning Gain

Group	N	Learning Gain (%)	SE
White Chinese	39	19.4	3.3
Vietnamese	153	19.4	3.1
White Japanese	35	19.1	3.3
White ARNL	15	19.0	3.6

NHPI Hispanic/Latino	14	18.9	3.3
Chinese Vietnamese	13	18.8	3.4
White Korean	20	18.6	3.5
NHPI	68	18.5	2.9
Asian	1134	18.4	2.7
Filipino	82	18.0	3.1
White Asian	19	17.9	3.6
White Filipino	54	17.8	3.3
Korean	91	17.7	3.0
Chinese	145	17.6	2.8
Asian Hispanic/Latino	20	17.6	3.3
White Asian Indian	21	17.5	3.8
Japanese	16	16.9	4.0
Asian Indian	259	15.6	3.5
ARNL	134	15.2	3.6
Avg.		18.1	3.3

Table V: The statistical results of learning gain across Asian social identity groups, including the number of student responses (N), learning gain, and standard errors (SE) for individual groups. Note: white color represents the monoracial groups, blue color represents the biracial groups, and green color represents the benchmark.

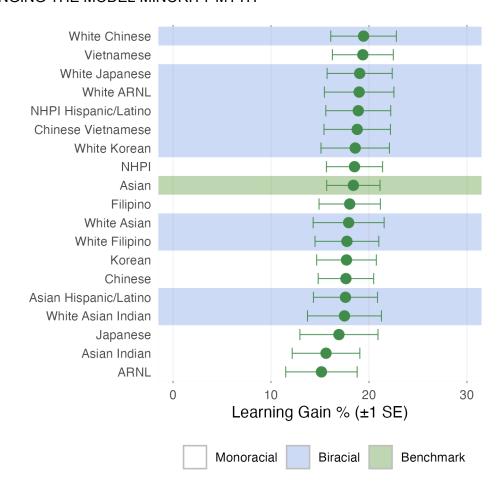


Figure 3: Learning gain across Asian identity groups. The error bars represent \pm 1 standard error.

Table V and Figure 3 show the averages and standard errors (SEs) of learning gains across the Asian groups. While the overall average learning gain was 18.1% (SE = 3.3), the predicted mean learning gains ranged from 15.2% (ARNL) to 19.4% (Vietnamese and White Chinese). There was significant overlap in the compatibility intervals across all groups.

Discussion

Our findings revealed large and meaningful differences in the predicted scores across Asian ethnic groups in introductory calculus-based physics courses. We analyzed performance differences between Asian groups in terms of "months of learning" (Kraft, 2020), where an 18 - 20% point learning gain on these physics concept inventory corresponds to approximately one semester of instruction (Nissen et al., 2022; Van Dusen & Nissen, 2022). In both tests, the difference between the NHPI Hispanic/Latino and Asian (benchmark) is approximately 10% points, corresponding to half a semester of instruction. The difference between the NHPI

Hispanic/Latino and White Korean is about 20%, equivalent to a whole semester of instruction. The disparity of 20% points in pretest and 19.6% points in posttest highlights the stark inequities that exist within Asian racial and ethnic groups, challenging assumptions of homogeneity in aggregated reporting.

All of the Asian identity groups had relatively close average gains from pretest to posttest, with largely overlapping compatibility intervals. Thus, while the instruction benefited all groups quite equally, it did not reduce the cross-group inequities, instead maintaining prior disparities.

Limitations

While our model reveals important disparities across Asian ethnic groups, our sample size limited our ability to represent all of the groups and the intersectional aspects of their social identities that we would like to include in this analysis (e.g., gender and first-generation college status). These factors vary across groups: for example, only 6.2% of Japanese students in our data identified as first-generation college students, compared to over 80% of Asian Hispanic/Latino students (see Table IX). In the institutional contexts, 56.2% of Japanese students attended R1 universities, while only 25% of White Asian Indian students did so (see Table X). Research has shown that these variables impact academic outcomes: first-generation college students often face systemic barriers to success (Jehangir, 2010), institutional type can shape access to resources and support (Kuh, 2010), and gender dynamics influence performance and retention, particularly in STEM fields (Ong et al., 2011). Future research should extend intersectional analyses, such as exploring interactions between gender and Asian ethnicity identities, to further examine the sources and structures of educational disparities.

Conclusions

By using MAIHDA alongside AsianCrit and QuantCrit frameworks, our study revealed large disparities in outcomes across Asian groups. While the high scores of Korean and Chinese students (both monoracial and biracial) reinforce the stereotype of the "high-achieving Asian student" associated with the problematic model minority myth, the differences in predicted scores between the highest- and lowest-performing groups reveal the heterogeneity among Asian groups. The within-group heterogeneity suggests the distinct educational experiences and needs across different Asian races and ethnicities. It is also important to note that each group's predicted mean represents a distribution of scores, with individuals performing both above and below that average, highlighting further diversity within every Asian group.

While our data cannot identify the specific causes of the disparities we observed, prior research points to the influence of migration histories, English language proficiency, and educational opportunities in shaping outcomes across Asian racial and ethnic groups. Moreover, complex patterns, such as the similar performance of Asian Indian and Vietnamese students

despite meaningful differences in immigration patterns, demonstrate that these inequities arise from intersecting factors beyond socioeconomic status alone. The high and less variable outcomes among White biracial Asian groups indicate that they receive some level of privilege from their Whiteness, reinforcing the role of intersectionality in shaping educational outcomes.

Our study indicates the power of disaggregated data to uncover patterns hidden by broad labels like "Asian" or "non-URM." Yet, increased disaggregation poses a tension on the methodology (e.g., smaller sample sizes, wider standard errors, and reduced interpretability). To navigate these tensions, researchers must balance granularity with statistical precision, guided by theoretical frameworks (e.g., QuanCrit), research questions, and other factors. The current LASSO platform's identity options enabled this finer-grained analysis, and our use of MAIHDA provided a powerful way to examine group-level heterogeneity. Data collection efforts can build the foundation for future dataset growth and cross-study aggregation by incorporating finer-grained identity options that advance equity-focused analyses.

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Appendix

Group	First collection date	Last collection date
White Korean	2020-08-24	2023-12-11
White Asian	2015-08-28	2019-12-13
White ARNL	2020-08-17	2023-12-09
White Chinese	2020-01-10	2023-12-07
White Asian Indian	2016-01-25	2023-12-05
Korean	2020-01-16	2023-12-12
White Japanese	2015-08-26	2023-12-12
Chinese	2020-01-21	2023-12-13
Chinese Vietnamese	2020-01-24	2023-12-07
White Filipino	2017-01-23	2023-12-13
Asian Indian	2015-08-28	2023-12-09
Asian	2015-08-26	2022-05-25
ARNL	2020-01-09	2023-12-15
Asian Hispanic/Latino	2015-09-07	2019-11-27
Vietnamese	2020-01-21	2023-12-15
Japanese	2020-01-24	2023-06-12
Filipino	2016-09-05	2023-12-07
NHPI	2015-09-14	2023-12-06
NHPI Hispanic/Latino	2015-09-07	2019-10-24

Table VI: Collection date of Asian groups.

Crown	Nur	nber of respon	ses
Group	Total	Pretest	Posttest
Asian	1134	997	677
Chinese	245	191	196
Asian Indian	259	197	187
Vietnamese	153	117	113
ARNL	134	102	109
Korean	91	75	69
Filipino	82	71	63
NHPI	68	54	52
White, Filipino	54	42	41
White, Japanese	35	27	31
White, Chinese	39	33	29
White, Korean	20	16	16
Asian, Hispanic/Latino	20	17	14
White, ARNL	15	12	13
White, Asianindian	21	18	12
Chinese, Vietnamese	13	12	11
NHPI, Hispanic/Latino	14	13	10
White, Asian	19	18	10
Japanese	16	11	9

Table VII: Information of Asian groups with cutting off at least 10 responses in pre- or posttest.

Coefficient	Estimate	Est. Error
Intercept	53.7	3.7
Asian	5.9	2
Chinese	3.7	1.8
NHPI	-1.9	2.1
Asian Indian	3.6	2.2
Vietnamese	2.8	2.2
Korean	9.2	2.5
ARNL	4.3	2.2
White	6.5	2.2
Filipino	-0.9	1.9
Japanese	0.9	2.5
Hispanic/Latino	-3	1.7
Test	18.2	2.6
Retake	2.1	0.5
FMCE	-13.5	1.8
ARNL Strata	-0.8	2.2
ARNL Strata, Test	-3	2.3
Asian Hispanic/Latino Strata	0.4	2.3
Asian Hispanic/Latino Strata, Test	-0.6	2.9
Asian Strata	-1	1.9
Asian Strata, Test	0.3	1.5
Asian Indian Strata	1.3	2
Asian Indian Strata, Test	-2.5	1.9
Chinese Strata	3.1	2
Chinese Strata, Test	-0.5	1.9
Chinese Vietnamese Strata	-0.1	2.3
Chinese Vietnamese Strata, Test	0.6	2.7
Filipino Strata	0.9	1.9
Filipino Strata, Test	-0.1	2.2
Japanese Strata	-0.7	2.3
Japanese Strata, Test	-1.2	2.9
Korean Strata	1.2	2.2
Korean Strata, Test	-0.4	2.1
NHPI Hispanic/Latino Strata	0.3	2.3
NHPI Hispanic/Latino Strata, Test	8.0	2.7
NHPI Strata	0.7	2.1
NHPI Strata, test	0.4	2.3
Vietnamese Strata	0.4	2.1
Vietnamese Strata, Test	1.2	2.1

1.2	2.3
0.8	2.7
0.5	2.3
-0.2	2.7
0.3	2.3
-0.7	3
1.5	2.2
1.3	2.5
0.5	2
-0.4	2.3
0	2.2
0.9	2.4
-0.4	2.2
0.4	2.7
	0.8 0.5 -0.2 0.3 -0.7 1.5 1.3 0.5 -0.4 0 0.9 -0.4

Table VIII. Model estimates and estimated errors.

		Gender (%)				First	
Group	N	Man	Woman	Non Binary/ Transgender	Missing Data	Gen (%)	
ARNL	134	70.1	28.4	1.5	0	42.5	
Asian	1134	64.5	34.9	0.4	0.2	38.8	
Asian Hispanic/Latino	20	70	30	0	0	82.5	
Asian Indian	259	63.3	36.3	0.4	0	22.6	
Chinese	245	63.3	35.9	0.8	0	41.6	
Chinese Vietnamese	13	84.6	15.4	0	0	53.8	
Filipino	82	70.7	25.6	3.7	0	18.3	
Japanese	16	56.2	37.5	6.2	0	6.2	
Korean	91	57.1	42.9	0	0	11	
NHPI	68	64.7	33.8	1.5	0	42.6	
NHPI Hispanic/Latino	14	57.1	42.9	0	0	46.4	
Vietnamese	153	64.1	33.3	2	0.7	47.1	
White ARNL	15	46.7	40	6.7	6.7	6.7	
White Asian	19	73.7	26.3	0	0	28.9	
White Asian Indian	21	47.6	47.6	0	4.8	7.1	
White Chinese	39	61.5	30.8	7.7	0	5.1	
White Filipino	54	61.1	35.2	1.9	1.9	24.1	
White Japanese	35	51.4	48.6	0	0	11.4	
White Korean	20	60	40	0	0	30	
Total	2432						

Table IX: Descriptive statistics for gender and first generation across Asian groups.

Group	Number of responses	Number of institutes	R1 (%)	R2 (%)	Other (%)
ARNL	134	30	41.8	33.6	24.6
Asian	1134	31	31.2	26.8	42
Asian Hispanic/Latino	20	9	25	25	50
Asian Indian	159	36	51	28.6	20.5
Chinese	245	34	54.7	18.4	26.9
Chinese Vietnamese	13	11	38.5	30.8	30.8
Filipino	82	22	23.2	50	26.8
Japanese	16	11	56.2	25	18.8
Korean	91	23	39.6	11	49.5
NHPI	68	18	17.6	23.5	58.8
NHPI Hispanic/Latino	14	11	21.4	28.6	50
Vietnamese	153	30	30.1	27.5	42.5
White ARNL	15	11	53.3	13.3	33.3
White Asian	19	10	36.8	26.3	36.8
White Asian Indian	21	12	57.1	23.8	19
White Chinese	34	21	48.7	23.1	28.2
White Filipino	154	24	40.7	25.9	33.3
White Japanese	35	19	45.7	25.7	28.6
White Korean	20	12	50	25	25

Table X: Descriptive statistics for institution types by students and institutions across Asian groups.

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