EI Exit Analysis for Dissertation

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Abstract

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Introduction

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Methods

Independent variables (IV): xxx

Dependent variables (DV): As you can see in Table 1, there are ten exit categories under three general exit reason "umbrellas" (Hansen et al., 2016):

Table 1: Table of Exit Reasons

Exit Reasons	Exit Category Codes
Program completion	Category (C) 1: A child is no longer eligible for Part C prior to reaching age three
Exit at age three	C2: A child is exiting Part C and has been determined to be eligible for Part B
Exit at age three	C3: Part B eligible, continuing in Part C
Exit at age three	C4: Not eligible for Part B, exit with referrals to other programs
Exit at age three	C5: Not eligible for Part B, exit with no referrals
Exit at age three	C6: Part B eligibility not determined
Not receiving services	C7: Deceased
Not receiving services	C8: Moved out of state
Not receiving services	C9: Withdrawal by parent (or guardian)

Not receiving services	C10: Attempts to contact the parents and/or child were unsuccessful

These ten reasons were collapsed into six reasons based on the scope of this study and for logistical reasons. For example, "Deceased" is beyond the scope of this study; one reason is not used in Oregon; multiple codes were similar in nature to each other:

- Attempts to contact unsuccessful
- Withdrawal by parent
- Complete/not eligible for Part B
- Moved out of state
- Part B eligibility not determined
- Part B eligible

Preparatory work: We prepared the data in a following manner:

1. Created an Excel sheet from the national and Oregon data sets
2. Imported Excel sheet into RStudio
3. Collapsed/removed DVs
4. Collapsed data from multiple years into one aggregated data by race

Data Analysis: We used chi-square goodness of fit test to understand associations between children's race and their EI exit reasons. Chi-square tests tell us if we can be confident that differences in counts and expected counts are not due to chance. In other words, chi-square tests can be used to evaluate if there is a statistically significant relationship between two dichotomous or nominal variable. However, they are not able to indicate the strength or the direction of the relationship (Morgan et al., 2020).

First, we ran descriptive analysis of the national data set as an omnibus test. For this, we used foundational statistical functions and chi-square to test our null-hypothesis; there is no associations between children's race and their exit reasons.

We then analyzed the association between the exit reason, "Attempts to Contact Unsuccessful", using similar analysis. For this portion, we looked at the association between two racial categories, Black/African American and White infants/toddler groups, with "Attempts to Contact Unsuccessful". We created 2x2 table for this analysis, complete with the total number of exits. This was used to analyze the odd ratio and Cohen's *h*. Odds ratio are commonly used for reporting the odds of one outcome between two independent groups (Morgan, et al., 2020).

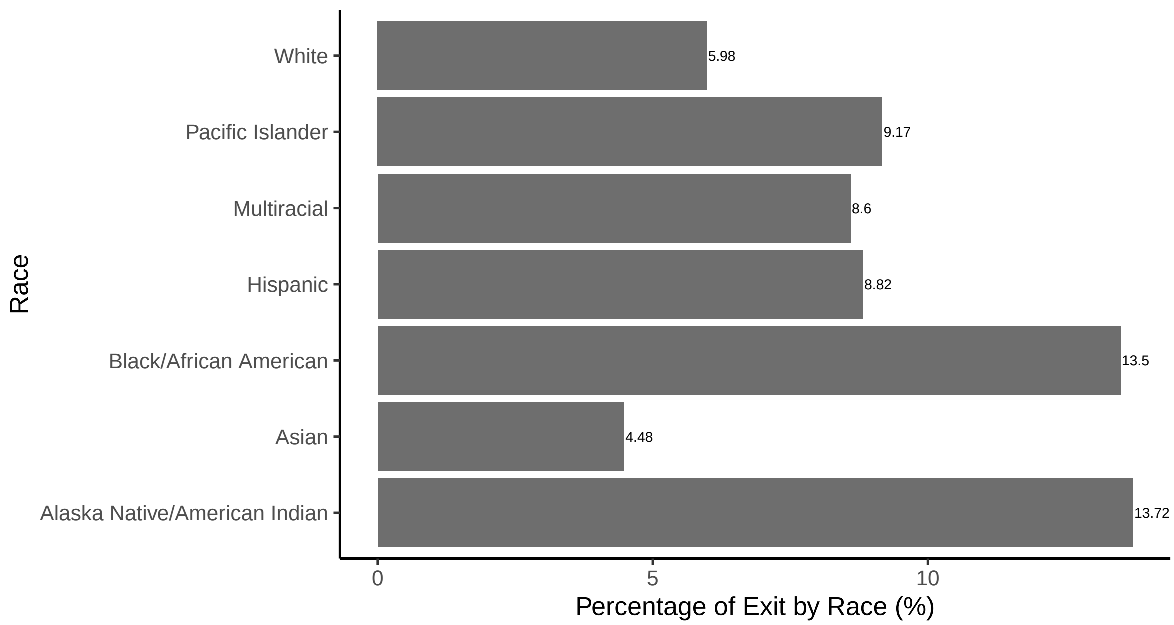
Results

The initial exploration included exit data from 3,310,559 children who exited the EI services between 2013 and 2022 nationally. Approximately 12.47% of the children were Black/African American, while 50.64% of the children were reported as being White. This shows a possible disproportionate representation of children, as census showed that during these years, Black/African American and White children represented approximately 14% for Black/African American children under the age of 18 and between 52% to 49 % for White children nationally (The Annie E. Casey Foundation, 2024). When looking at children under the age of six in 2022, the disparities widen: White children represented only 46.5% nationally, while Black/African American children represented 12.7% of the children under the age of 6 (Schneider & Gibbs, 2023).

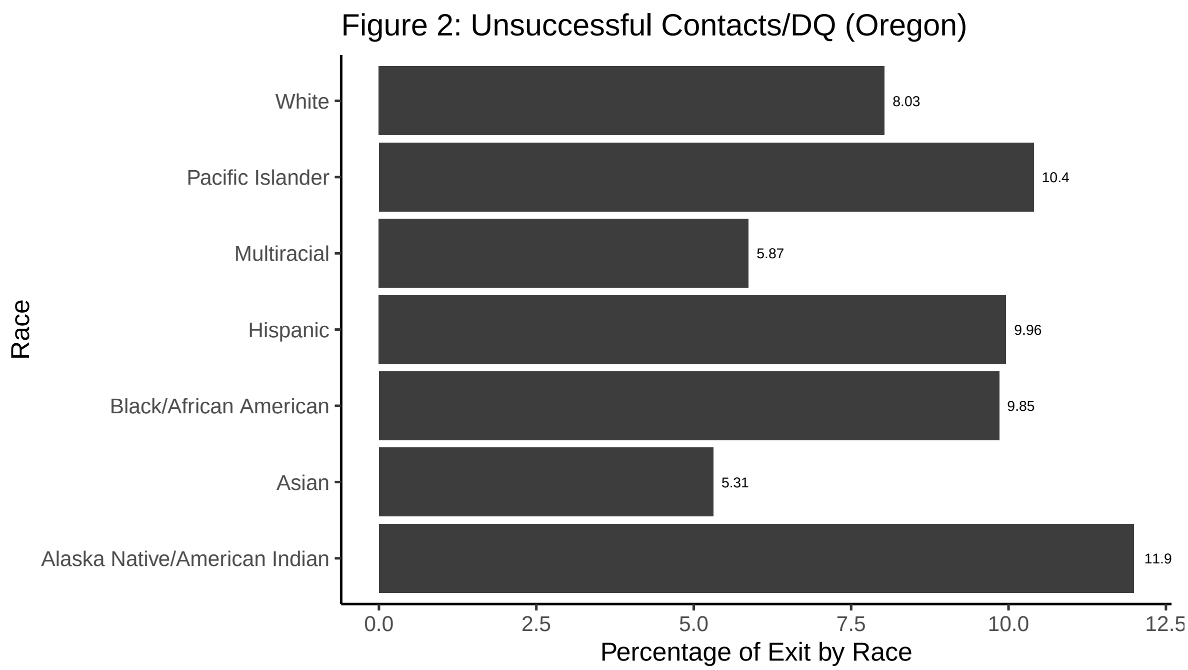
The chi-square omnibus test indicated that there was a statistically significant association between children's race and their exit reasons, X-squared (30, N = 3,310,559) = 52218.3, with a p-value of < 0.001

Looking specifically at the "Attempts to Contact Unsuccessful" category, approximately 13.5% of Black/African American infants and toddlers were disqualified from EI services nationally due to agencies losing contact with families, while only about 5.98% of White children were disqualified for the same reason (Figure 1).

Figure 1: Unsuccessful Contacts/DQ (U.S.)



When we look at the data at state level, the numbers change slightly. Approximately 9.85% of Black/African American infants and toddlers were disqualified from EI services in Oregon due to agencies losing contact with families, while only about 8.03% of White children were disqualified for the same reason in Oregon (Figure 2).



The chi-square indicated that there was a statistically significant association between children being Black/African American or White and them leaving EI due to being disqualified nationally. The chi-square test indicated, X-squared (222556.00, N = 2,088,058), p < 2.2e-16 or 0.0000000000000002 (p < .001).

Because whether or not children were Black/African American or White and whether they were likely to be disqualified from EI services due to "Attempts to Contact Unsuccessful" were both binary variables, we computed an odds ratio as well.

In order to calculate the odds ratio to determine the relative likelihood of the students being disqualified between the two groups, a 2x2 contingency table in a matrix format was created and analyzed. The odds of Black infants and toddlers being disqualified from EI services due to "attempts to contact unsuccessful" were significantly higher than those for White infants and toddlers, with an odds ratio of **2.46** (95% CI [2.43, 2.48]). This indicates that Black students were approximately 2.46 times more likely than White students to be disqualified from EI services for this reason.

Cohen's h was calculated to evaluate the effect size of the analysis. The result indicated a small to medium effect size, $h = 0.259$. However, even though effect size shows the magnitude of the difference, it is not necessarily considered to be a direct indication of the importance of the findings (Morgan et al., 2020).

Discussion

Our analysis revealed that the odds ratio for Black/African American infants and toddlers to be disqualified from EI services due to "Attempts to Contact Unsuccessful" was 2.46 times higher when compared to their White peers nationally. In addition, state-level data showed smaller disparities between disqualification rates between Black/African American children and that of their White peers. However, there are many limitations to this descriptive analysis.

First of all, we have to remember that race is not a predictive factor for outcomes. At a quick glance, race seems to be associated with inequity in EI service exit patterns. However, research following the completion of the Human Genome Project has shown that race, from a genetic standpoint, does not contribute to health inequities. Instead, it is the environments experienced by racially minoritized communities that play a significant role (Silverstein, 2015). Silverstein cited Kittles (2015) in order to clarify this: "the bulk of those disparities are not due to any biological difference. The vast majority of health disparities are due to social, behavioral, and environmental components". Race is merely one of the many descriptors for individuals.

In addition, as Crenshaw (1989) established in her seminal work, we must take the framework of Intersectionality when conducting a research. This type of oversimplified statistical analysis can contribute to reinforce the status-quo where race is quickly to be blamed, rather than the complex environments and multiple layers of identities that members of marginalized communities live in.

The smaller disparity between racial groups in Oregon in terms of disqualification rate could be due to the state's limited diversity, meaning we simply don't have enough data. This makes it challenging to conduct quantitative studies on marginalized populations, even though research is so urgently needed for that very reason.

Last but not least, researchers have argued that quantitative methods are inequitable, as "the history of quant methods is inseparable from eugenics movement" (p. 4, Castillo & Strunk, 2024) and that it stems from and reinforces inequity. QuantCrit philosophy are based and expands on the centrality of racism and the lack of neutrality in numbers and categories. Going forward, it would be extremely important to remember these tenets and to approach data collection, categorization and analysis with equity and justice as the central philosophy.

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