Received: 15 April 2021 | Revised: 26 April 2023 | Accepted: 28 April 2023

DOI: 10.1002/jee.20530

REVIEW ARTICLE

JEE
Journal of Engineering Education

Person-centered analyses in quantitative studies about broadening participation for Black engineering and computer science students

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Funding information
National Science Foundation, Grant/Award Numbers: EEC-1647327, EEC-1926935

Abstract

Background: There have been calls to shift how engineering education researchers investigate the experiences of engineering students from racially minoritized groups. These conversations have primarily involved qualitative researchers, but an echo of equal magnitude from quantitative inquiry has been largely absent.

Purpose: This paper examines the data analysis practices used in quantitative engineering education research related to broadening participation. We highlight practical issues and promising practices focused on "racial difference" during analysis.

Scope/Method: We conducted a systematic literature review of methods employed by quantitative studies related to Black students participating in engineering and computer science at the undergraduate level. Person-centered analyses and variable-centered analyses, coined by Jack Block, were used as our categorization framework, backdropped with the principles of QuantCrit.

Results: Forty-nine studies qualified for review. Although each article involved some variable-centered analysis, we found strategies authors used that aligned and did not align with person-centered analyses, including forming groups based on participant attitudes and using race as a variable, respectively. We highlight person-centered approaches as a tangible step for authors to engage meaningfully with QuantCrit in their data analysis decision-making.

Conclusions: Our findings highlight four areas of consideration for advancing quantitative data analysis in engineering education: operationalizing race and racism, sample sizes and data binning, claims with race as a variable, and promoting descriptive studies. We contend that engaging in deeper thought with these four areas in quantitative inquiry can help researchers engage with the difficult choices inherent to quantitative analyses.

KEYWORDS
data analysis, person-centered approaches, quantitative, race/ethnicity, undergraduate, underrepresented students

1 | INTRODUCTION

> *Creating a workforce that is capable of thinking and working across diverse perspectives is imperative to the future of engineering. To achieve this goal, we must characterize diversity, build communities that value diversity, and develop programs and initiatives to leverage diversity*.(The Research Agenda for the New Discipline of Engineering Education, 2006, p. 261)

In 2006, the *Journal of Engineering Education* published a special report outlining a research agenda for the field, in which "Engineering Diversity and Inclusiveness" was positioned as a central research area. According to this agenda, the essential research tasks for creating the workforce needed to tackle the grand challenges of tomorrow were (1) characterizing what the field means by *diversity*, (2) constructing and maintaining engineering cultures that uphold principles of inclusiveness, and (3) creating programs that infuse the benefits of diversity ("The Research Agenda," 2006). As the years have passed, the engineering education research community has nurtured a shared commitment to including students across racial and gender spectrums in their research.

Engineering education researchers aim to enhance the field's understanding of how different student groups are affected by instructional interventions, policies, and other structural barriers to participation. Accordingly, the quantity of research focused on these ideas has grown into a flourishing research area (i.e., research on broadening participation in engineering). However, because the amount of research does not indicate progress alone, it is essential that the field periodically reflect on what has been done and decide if it is working toward the desired impact. As relevant to this publication venue, Pawley (2017) and Holly (2020) offer such reflections in their *Journal of Engineering Education* editorials.

First, Pawley (2017) argues to "shift the default" from one where the merits of diversity must be argued in journal manuscripts—requiring authors to spend precious page space presenting well-articulated positions already codified in the discipline's agenda ("The Research Agenda," 2006)—to a new default in which all empirical studies involving people should be expected to report racial and gender-specific demographic information. Pawley contends that the additional demographic information would enable readers to better evaluate generalizations made in engineering education studies. Specifically, readers can infer the extent to which the conclusions are bound to the majority participating population, that is, White men or boys. In Pawley's (2017) view, the new default would make "Whiteness and maleness" explicit and expose "where women and men of color and white women are quietly being excluded" (p. 532).

Second, Holly (2020) offered his reflection on the need to disentangle engineering education research's anti-Blackness. A central argument in his editorial is that "engineering education research in its current form is largely enmeshed in a perpetual undermining of Black scholarship and life" (p. 632). In particular, he argues that selecting a research methodology can be an explicit step where engineering education researchers can embed a pro-Black lens into their approaches. In Holly's view, engineering education must pay more attention to the arrangement of the power dynamics associated with particular methodologies. We are challenged to choose methodologies where participant–researcher interactions are equitable rather than focusing on methods that create datasets we consider rich at peoples' expense.

Holly's point is echoed by Godwin (2020), where she highlights the process of co-constructing meaning instead of simply taking data from participants—underscoring the researchers' role in meaning-making by stating, "we leave our research fingerprints all over our work" (p. 79). In adopting pro-Black research methods, it is essential for engineering education researchers to review their positionalities such that power differentials can be brought to light and interrogated thoughtfully before engaging in the planned study (Godwin, 2020; Hampton et al., 2021; Secules et al., 2021). This mindfulness in co-constructing versus taking data from participants is embedded in the process of ethical validation (Walther et al., 2015), a quality process in which the researcher mitigates the risk of misconstruing social reality as manifested in the data.

1.1 | Research aim—Curating strategies to engage with quantitative research critically

Although the aforementioned reflections primarily concern qualitative inquiry, this paper examines how researchers account for race in quantitative engineering education research related to broadening participation for Black students, building most explicitly on the initial work done by Godwin et al. (2021). We contend that more work is needed to understand how to more thoughtfully engage in equitable, reflective quantitative research due to the intrinsic features of quantitative approaches. Moreover, Coley et al. (2021) argue that "there is a critical need for DEI [diversity, equity, and inclusion] literature to be reviewed in a systematic way" and add that "existing articles lack the specific focus of DEI and insights on how DEI intersect with engineering education" (p. 11). Accordingly, we completed a systematic literature review on the current state of methods used in scholarship on Black students in undergraduate engineering and computer science education. We limited the methods employed in these articles to quantitative inquiry. In addition, we searched for studies that disaggregated their results by race to spotlight articles that put race into focus. After reviewing the articles using concepts advanced by Godwin et al. (2021) in engineering education, that is, person and variable-centered approaches, we backdropped the analytical decisions with the tenets of QuantCrit (Gillborn et al., 2018). We show how person-centered approaches can be used to begin engaging with more critical quantitative work.

Therefore, to ground our work, we'll begin by describing the premise of person-centered and variable-centered approaches, followed by outlining the principles of a larger overarching framework for engaging in critical quantitative research (i.e., QuantCrit), and finally, close by mapping the principles that compose the idea of person-centered approaches to QuantCrit's tenets.

1.2 | Categorization framework: Person-centered and variable-centered approaches

The distinction between person and variable-centric approaches is traceable to Jack Block (1971); only recently has the terminology appeared in engineering education. Variable-centered approaches answer questions related to prediction, such as "What is the impact of a summer bridge program on the retention of first-year engineering students to the second year?" On the other hand, person-centered approaches ask descriptive questions, such as "What are the common characteristics of students in the second year of engineering who do and do not participate in co-curricular programs?" Both are necessary to advance the status of knowledge; however, it is unclear to what extent person-centered approaches have been explored in engineering education.

The descriptor of variable-centered or person-centered is not necessarily inherent to the method itself—it encapsulates the research goals and analytical decisions to achieve the stated goals. Accordingly, a variable or person-centered approach can be further delineated by how "difference" is handled among groups. Quantitative researchers will likely be most familiar with a standard method of addressing "difference" in a dataset, *outliers*. Many traditional statistical tests involve calculating a mean or average, and it is well known that extreme values—the outliers—substantially impact the average value. For example, engineering education researchers who routinely use regression-based analyses must screen their data for outliers because data points that lie too far away from the others have a nontrivial effect on the best-fit line or hyperplane.

Instead of removing individuals from the dataset, the categories to which they belong can be tweaked to bin them into bigger groups. This common practice is employed to increase the statistical power of the test being applied, which ensures that the test correctly rejects the null hypothesis with greater probability. Consider a scenario where a researcher wants to assess the impact of a spatial thinking program for different racial groups using a repeated-measures ANOVA. Suppose there are low numbers of students identifying as Hispanic and Black in the dataset (commonly used labels). In that case, the demographic categories of Hispanic and Black may be binned into a single category to make the sample size (closer to) equal to the White comparison group. A person-centered approach would not look at these demographic categories to balance the size of the subgroups. Instead, person-centered approaches aim to capture a more holistic perspective of the dataset by maintaining variation across measurements and focusing on non-superficial labels of groups that could address issues of small sample sizes in specific subgroups (Laursen & Hoff, 2006; Morin et al., 2018).

To summarize, a person-centered approach to analysis embraces heterogeneity in the dataset (i.e., it is not necessary to form aggregate bins), whereas a variable-centered approach privileges homogeneity—that is, minimizing outliers to conform to distributional assumptions such as normality. The distinctions between these two approaches are highlighted in Table 1.

1.3 | The principles of QuantCrit

To join the dialogue about shifting the default and pro-Black approaches flourishing in the qualitative space and permeating quantitative inquiry, we turn to QuantCrit. The term QuantCrit, coined by Gillborn et al. (2018), captures the application of Critical Race Theory to quantitative research approaches. QuantCrit is not a theory; the authors

TABLE 1 Summary of person-centered and variable-centered approaches (Laursen & Hoff, 2006).

Variable-centered	Person-centered
Variables are the agents that affect change, and people are the instruments through which they operate—prefers homogeneity	Variables are properties of individuals and their environments—embraces heterogeneity
Concerned with prediction, capturing the strength and reliability of predictors	Concerned with description, identifying latent or theory-driven trajectories within individuals based on properties who share similar attributes
Most useful for general principles connecting variables over time, but difficult to generalize for heterogeneous populations	Most useful for understanding how larger principles impact latent subgroups with similar attributes, good to dig into smaller, potentially theoretically meaningful, groups.

describe their approach as a framework or toolkit to interpret quantitative research results. To date, it has not been widely applied in engineering education contexts beyond a selection of studies with a broader STEM framing (e.g., Priddie, 2021; Suárez et al., 2021). The framework is embodied by the following five principles given by Gillborn et al. (2018):

1. The centrality of racism; this principle asserts that racism is a pervasive component of society that is difficult, or even impossible in the opinion of some scholars, to quantify (Garcia et al., 2018). The researcher must be cognizant of how data collection and analytical procedures can be biased toward the "racial status quo" (Gillborn et al., 2018, p. 170).
2. Numbers are not neutral (Ladson-Billings, 2021); quantitative evidence is gathered *and* analyzed within a framework chosen by the researcher. Whether produced by the researcher or from another source, choosing relevant evidence involves determining how to quantify the phenomenon of interest.
3. Categories are neither natural nor given; treating race/ethnicity as given, whether as a categorical variable or groupings, can flatten the experiences of a group down to an immutable characteristic without considering other dynamic influences on a group's experience (Holland, 2008). This flattening is evident in White versus the often heterogeneous group labeled "non-White" or "underrepresented"—which tacitly asserts that the non-White group is homogenous and its members share analytically equivalent experiences.
4. Data cannot speak for themselves; with the proliferation of claims of using big data—whether authentically or fallaciously—for decision-making, the inductive nature of the analyses can lead researchers to claim value-free inferences. However, as articulated in principle two, numbers are not neutral and are constructed through valued judgments. Moreover, this principle asserts that data are inert objects that require interpretation—of which there are often several possible interpretations.
5. Social justice and equity orientation; building off principle four, QuantCrit does not endorse political neutrality in statistical applications. Rather, it encourages researchers to work "with and against numbers" (Gillborn et al., 2018, p. 174). That is, we should engage statistics with care to avoid upholding deficit framing frameworks (cf. Covarrubias & Vélez, 2013) and the misuse of quantitative methods.

These principles serve as a guiding framework for this study as we apply them to engineering education research articles. We focused on analytical decisions to pinpoint salient takeaways for engineering education researchers to engage more thoughtfully in racially sensitive quantitative research. We place so much emphasis on analytical decision-making because it is one of the key points at which troublesome but accepted practices can occur; our goal here is to spotlight them.

1.4 | Tying person-centered analyses to QuantCrit

We contend that adopting a person-centered approach can be a meaningful step to engaging in QuantCrit; to illustrate, we'll outline some intersections between person-centered approaches and QuantCrit. First, person-centered approaches aim to recognize heterogeneity and preserve variation, which aligns with the "Categories are neither natural nor given" principle of QuantCrit. Such analyses create inclusive groupings that can better match the variation in student responses and fluid characteristics. Similarly, a person-centered approach meshes with QuantCrit's first principle, "the centrality of racism," because, as Gillborn et al. (2018, p. 170), explain: "the heart of [QuantCrit] is an understanding that 'race' is 'more than just a variable' (Dixson & Lynn, 2013, p. 3)." By moving beyond race as a static quality and recognizing that, as Apple (2001) states, "race is a construction, a set of fully social relationships" (p. 204), person-centered approaches provide a mechanism for representing socially constructed and dynamic relationships.

On the other hand, person-centered approaches can easily violate the "numbers are not neutral" and "data cannot speak for themselves" principles of QuantCrit if researchers are not careful. For instance, they can potentially be used to avoid discussions of race by over-relying on inductive labels that are advanced as de facto categories inherent to students. Notwithstanding that these approaches could be used nefariously or irresponsibly, person-centered approaches can provide researchers with latent groups irrespective of immutable traits like race or ethnicity. For example, a popular technique used in engineering education called cluster analysis could be used to find groups with some intrinsic shared characteristics that are analytically meaningful and would otherwise not have been found if static demographic bins were used to segment the data (Garcia-Dias et al., 2020). These latent groups can then be used to contextualize demographic categories.

It should be emphasized that person-centered and variable-centered approaches do not form a dichotomy (Magnusson, 1988); they are complementary. Just as with the fifth principle of QuantCrit of working with and against numbers, quantitative methods must be used responsibly to engage with the structural barriers researchers in engineering education aim to dismantle. Together, they offer two valuable perspectives on a phenomenon; however, Laursen and Hoff (2006) urge that the combinational "potential cannot be realized unless scholars ask research questions that draw upon the complementary nature of the two approaches." (p. 385). Therefore, for quantitative work in engineering education to advance pro-Black and antiracist approaches, it is suggestive that a balance in variable and person-centered approaches be sought.

With this perspective of person-centered analyses, we will move into our study to understand how engineering education researchers account for race in their work on broadening participation in computer science and engineering.

2 | METHODOLOGY

This scholarly work's contributions result from a systematic literature review (SLR). SLRs are used to summarize, critically evaluate, and reconcile conflicting evidence to inform policy and practice (Borrego et al., 2014). SLRs may vary in purpose from describing the current state of knowledge, evaluating theory, and identifying gaps in the literature (Petticrew & Roberts, 2008). The five major steps of this SLR include:

1. Formulate Guiding Research Questions and Corresponding Inclusion Criteria.
2. Find and Catalog Sources.
3. Critique and Appraise the Quality of Selected Literature.
4. Synthesize Insights.
5. Address Bias, Validity, and Reliability Concerns.

These steps serve as the organizing framework for this Methodology section.

2.1 | Formulate guiding research questions and inclusion criteria

In response to the aforementioned calls for more thoughtful practices regarding race in engineering education across journals, we pivoted an ongoing research effort that began in 2017 to join researchers who have specifically laid the groundwork for this discussion in quantitative engineering education research. In particular, as a response to Martin and Garza's (2020) work, Godwin (2020) authored a piece to contextualize the task of "challenging whiteness in quantitative research" (p. 78). She calls for researchers to:

> engage in the discomfort of sitting in the tension of our roles and decisions as researchers through coloring epistemologies, identifying and challenging White supremacy characteristics in our work and practice. (p. 81)

Her response to Martin and Garza (2020) shaped our research process and brought us to this paper, spotlighting specific decisions employed by engineering education researchers in quantitative studies about broadening participation in engineering. Accordingly, we intentionally review the data analysis practices in prior quantitative engineering education research and offer recommendations for the community moving forward related to accounting for race using the concept of person-centered analyses (Block, 1971; Godwin et al., 2021; Laursen & Hoff, 2006; Morin et al., 2018).

We contend this work is a tangible step in moving the community toward engaging with quantitative research more thoughtfully. Upon learning the myriad issues regarding mixing quantitative research with race, especially considering its messy ties with eugenics (Louçã, 2009), questioning whether quantitative methods belong in our toolkit is a potential reaction. Like Godwin (2020), we do not believe traditional statistics should be abolished. Instead, we posit that one key to this work is illustrating the issues within the analytical stage of quantitative engineering education publications on broadening participation so we can engage in these practices more reflectively. Thus, the questions guiding this study were: (1) *How does quantitative scholarship in engineering education align with the principles of person-centered analyses regarding its treatment of race?* and (2) *How can future scholarship on race that relies on quantitative methods be improved to better account for the methodological considerations of race?*

To establish the earliest publication date for our review, we turned to landmark developments in the 1970s related to increasing the number of Black students in engineering and computer science. In particular, the founding of national-level efforts related to broadening participation in engineering, such as the National Action Council for Minorities in Engineering, Inc. (NACME) in 1974 and the National Society for Black Engineers (NSBE) in 1975. These efforts served as a lower bound year-wise for which research in broadening participation would gain momentum. We set the review's upper bound for publication year to the present day when we collected the papers in January 2017. Therefore, the date range was 1975–2017. The other criteria will be discussed in the next section.

2.2 | Find and catalog sources

A librarian assisted our research team by performing database searches and developing a search strategy that limited publication bias. Before conducting the review, search strings were validated using *sentinel articles*. Sentinel articles are chosen by the researcher(s) to maximize the number of relevant articles in the search while minimizing the number of articles not fitting the review's goal by refining keywords extracted from the sentinel articles (Phillips et al., 2017). Fourteen sentinel articles served as benchmark publications used during preliminary checks. For example, the sentinel article, *"You would not believe what I have to go through to prove my intellectual value!" Stereotype management among academically successful Black mathematics and engineering students*, by McGee and Martin (2011), was picked because of its relevance to a mapping review that preceded this SLR. More specifically, McGee and Martin's (2011) work fit within the following three inclusion criteria:

1. Is the article written in English and about education or the STEM workforce in the United States?
2. Is the article focused on engineering or computer science in any context or STEM disciplines in a K–12 context?
3. Is the article focused on issues or the experiences of Black students or on some aspect of the wide variety of topics associated with broadening participation? (One of our previously published articles includes reflections on the "messiness" of executing these initial, value-laden steps of an SLR, using this project as an example (Phillips et al., 2017).)

Table A1 in Appendix presents the final list of databases, search strings, and notes that may be useful for replicating the search. In our search strings, we used the term Black and African American. We recognize that the terms Black and African American are not equivalent; however, they are often used interchangeably in the literature. We use the term Black throughout the manuscript to align with Holly's (2020) call for pro-Black approaches in engineering education.

Three coders analyzed each article, meeting when needed to discuss articles that required an additional opinion. In total, 470 out of 1180 (40%) articles met the three eligibility criteria. Further details on the initial mapping review can be found in another publication (London et al., 2020). This SLR is a subset of the larger mapping review. In this case, we focused on studies with a target population of undergraduate students and used quantitative methods as their analytical approach for this particular SLR. Thus, we had two additional criteria to filter out irrelevant articles from the mapping review.

4. Does the article use quantitative methods?
5. Is the article focused on undergraduate students as its target population?

Additionally, we excluded assessment-focused papers from this review. As a result, this SLR is more focused on generalizable research rather than classroom-specific interventions. A separate publication focuses solely on relevant interventions and assessments (Holloman et al., 2021). Figure 1 depicts the PRISMA flowchart associated with this SLR. Table A2 in Appendix A contains the coding procedure used to organize the articles. Finally, the full list of articles can be found in the supplementary materials (Table S1).

2.3 | Critique and appraise the quality of literature

Following the documentation of the mapping review results, the manuscripts associated with undergraduate education went through a quality check. In general, quality checks require researchers who conduct SLRs to ensure critical aspects of a research study are present such that the trustworthiness of the findings can be judged accuractely. Four questions determined whether a study passed the quality threshold and was included in this SLR. Each question required a yes or no response. The questions were as follows:

1. Is the study's problem/purpose/aim clearly stated, and is it focused on undergraduate education?
2. Is the sampling strategy apparent and appropriate? That is, does the sample represent the target population, and is it congruent with the research question?
3. Is information about data collection procedures apparent and appropriate?
4. Is information about the approach to analyzing data apparent and appropriate for addressing the study's purpose?

Ultimately, 49 articles passed the final quality check, resulting in a set of articles that used quantitative methods and were focused on undergraduate education. Notably, only one manuscript from the *Journal of Engineering Education* remained in our review.

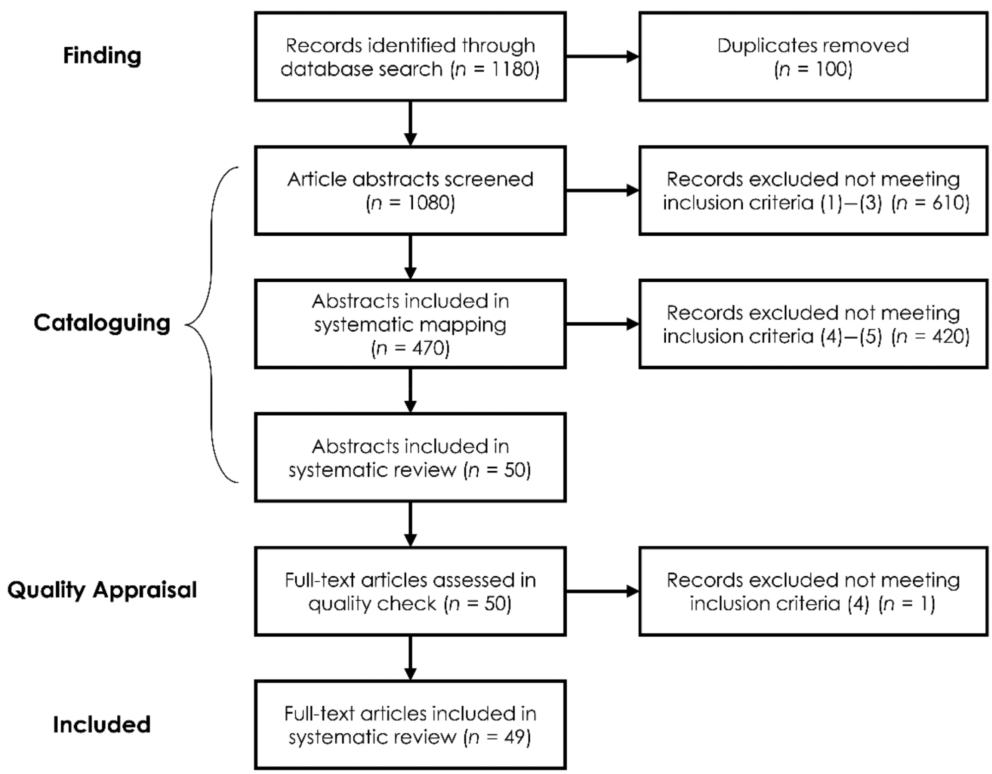

FIGURE 1 PRISMA flowchart for SLR.

2.4 | Synthesize insights

We approached the articles in our dataset with the person/variable-centered lens to examine how articles that were disaggregated by race approached the concept of "difference" in their analyses. Thus, we searched for person-centered approaches through the examined studies' research questions and analyses across four dimensions (note, principles two and five were combined due to space limitations and their intersecting topics) as our analytical approach. The following four questions frame how we envisioned the principles of QuantCrit *as relevant to our discussion of person-centered analyses* in the context of the manuscripts explored in the current study is given in Table 2.

2.5 | Address bias, validity, and reliability concerns

Existing research outlines various steps to address bias, validity, and reliability concerns while conducting an SLR (Mullen & Ramírez, 2006). This section describes how those guidelines were implemented in this work. To minimize bias traditionally stemming from authors electing to report only certain outcomes and/or studies with only positive results, search techniques that consider gray literature (and not just journal publications, for example) were employed (Higgins et al., 2019). As mentioned, a librarian was involved in identifying keywords and databases to mitigate the impact of researcher bias. Accordingly, primary studies were masked by the librarian for author names, affiliations, and journal names during the quality appraisal phase to avoid selection bias.

Furthermore, this article and other SLRs associated with this project thoroughly explain the methodology used to identify and collect data; this has been described above to showcase consistency and transparency. Additionally, multiple coders were used to apply and discuss criteria for inclusion/exclusion and quality assessment to help establish reliability and further minimize bias in segmenting the mapping review in individual SLRs on specific topics, such as K–12, undergraduate, and graduate education. Collectively, these efforts were designed to address concerns that may stem from questions about bias, validity, and reliability.

2.6 | Limitations

To close our discussion of the methods, we will outline the limitations present in this study. According to Cook et al. (1997), the limitations of a systematic literature review stem from (1) the quality and quantity of the selected studies and (2) the quality of the systematic review procedures. In this study, we were interested in the literature on Black

TABLE 2 Summary of SLR questions related to QuantCrit principles.

QuantCrit principle(s)	Questions in SLR related to the principle
The centrality of racism	Given the problematization of the quantification of racism in the QuantCrit literature, "How do articles incorporating a person-centered approach employ quantitative analyses that are sensitive to race/racism?"
Categories are neither natural nor given	From QuantCrit's principles, treating race as a given category can ignore the broader social dimension of what it means to be a certain race, so "to what extent does the analysis treat race as an independent variable in a variable-centered fashion?"
Data cannot speak for themselves	QuantCrit asserts that all data require interpretation. To arrive at those conclusions, we explore the question, "how do the authors draw inferences from choices in binning racial categories in a person-centered/variable-centered approach?"
Numbers are not neutral and social justice/equity orientation	QuantCrit asserts that quantitative evidence is gathered and analyzed within a framework chosen by the researcher, which involves a push and pull with the assumptions underlying the method. Accordingly, we explored our final question, "what kind of studies are done regarding race using quantitative perspectives (i.e., how are numbers used to advance arguments regarding race), and for what purpose?"

undergraduate engineering and computer science students. With this in mind, literature solely about Black undergraduate students in general or undergraduate students in engineering, did not meet our inclusion criteria and were excluded as a result. We acknowledge that this choice will lead to the possibility that this SLR is not comprehensive of all literature related to the target population. The compound inclusion criterion is a limitation of our interest in scholarship specifically focused on the intersecting identities of being Black and an undergraduate engineering student.

Furthermore, the fact that the review's topic has not been consistently studied since 1975 led to a small quantity of articles and, by extension, more opportunities for future research than insights from the existing scholarship. Lastly, because the literature in this review was collected in January 2017, the length of typical publication cycles may have excluded more recent articles. However, with calls for more critical quantitative scholarship only recently emerging with prominence, it is unlikely that these practices have been integrated into the community's collective consciousness.

Given this scope of the study and the need to identify articles at the intersection of a set of topics—that is, undergraduate education AND African Americans/Black AND engineering OR computer science—we acknowledge that there may be other literature that is peripherally relevant because of its focus on either of the topics. However, we consider these articles beyond this SLR's scope without emphasizing all three topics simultaneously. We also recognize the scope of the study excludes other People of Color, such as Verdín's work with first-generation Latina students (e.g., Verdín & Godwin, 2018). Moreover, because of the choice in search strings, articles that examined specific parts of the Black experience may have been omitted.

2.7 | Researcher positionalities

Before delving into our results, it is critical to disclose our positionalities in this work to advance the practice (Godwin, 2020; Hampton et al., 2021; Secules et al., 2021), considering the combination of researchers on this article.

The aim of this paper directly informed the composition of our research team. Motivated by a funded project led by Walter and Jeremi, this effort's original goal was a systematic literature review not necessarily focused on research quality. Walter is a Black man, and Jeremi is a Black woman. Both authors have spent multiple years prior to writing this manuscript focused on efforts to broaden the participation of Black Americans in engineering and computer science. David was originally invited to lead an analysis that heavily relied on his methodological expertise, quantitative research. The purpose of the review was to summarize the insights from a subset of papers in the mapping review that used quantitative research methods. David is a White man who approaches the research process through a critical realism worldview—his positionality in generality has been documented in several locations (e.g., Hampton et al., 2021; Hampton & Reeping, 2019).

During David's initial pass through the manuscripts, discomforts about the methods used to study this population's outcomes bubbled to the surface because of his position as an outsider. Though the practices employed by the authors in the manuscripts are commonly accepted as a routine within the conventional framework of quantitative research, something did not seem right. For instance, as he reflected more deeply on his expertise, one practice that seemed odd was including the variable "race" in a regression model as a dummy variable-mathematically, this seemed to play the game of "what would have happened if the person was [this race]." These little nudges persisted as he reviewed more manuscripts.

After a meeting of all three authors to discuss the review's progress, we decided to shift our focus to approaching the review aiming to deconstruct current practices in quantitative methods in broadening participation research, after which Walter lent David his copy of *White Logic, White Methods* (Zuberi & Bonilla-Silva, 2008). This first deep dive led to an internal critique of David's applications of quantitative methods that fundamentally transformed how he viewed quantitative research, leaving him in a liminal state and writing early versions of this manuscript to be an arduous task. He reflected throughout the review process through the lens of the conversations in the engineering education literature—that is, Godwin (2020), Holly (2020), and Pawley (2017)—expanding into the QuantCrit body of literature in conjunction with Jeremi and Walter.

Although David is an outsider to the population of interest that initially motivated this study, he affirms his commitment to diversity and inclusion in this manuscript by offering quantitative expertise to improve how we apply quantitative methods to race-related topics in engineering education. Together with Walter and Jeremi, this paper's team members complemented one another's strengths to synergize into a new addition to the conversation bustling within the engineering education research community. He encourages readers to engage with the editorials referenced throughout this article and the work of Black scholars generally; this review is just one piece of a dynamic movement in engineering education to better understand and conceptualize race in our work.

3 | RESULTS AND DISCUSSION

We organized the discussion of our results by drawing from the principles of QuantCrit to understand how studies focused on broadening participation for Black students employed person-centered analyses. Although we focus on the authors' person-centered approaches, this does not mean variable-centeredness was not present. Considering most researchers are likely well-acquainted with variable-centered approaches already, the strategies we discuss can be seen as complementary to existing engineering education research practices—or revisions to them.

Following our survey of the person-centered approaches found in the sample, we turn to a broader commentary on person-centered analyses. To situate our results of person-centeredness in the analyses, we draw upon the principles of QuantCrit to weave into our discussion on how the articles aligned with its principles in terms of analytical decision-making. We also advance the discussions about race and research presented by Pawley (2017), Holly (2020), Martin and Garza (2020), and Godwin (2020) where appropriate. In particular, we focus on the following issues: *operationalizing race and racism*, *sample sizes and data binning*, *claims with race as a variable*, and *engaging with descriptive studies*.

3.1 | Person-centered approaches in the sample

Our review of the sample brought forth a multitude of variable-centric approaches to studying race in engineering education; most articles do not dig deeper into groups to identify trends across latent characteristics. A summary of the approaches gleaned from our sample is given in Table 3. It is somewhat tricky to parse the type of research design in several manuscripts because doctoral theses were included, which often had several types of analyses embedded within them. Still, the most common approaches were different types of regression (linear $n = 19$, hierarchical $n = 7$, logistic $n = 6$), descriptive statistics ($n = 14$), and analyses designed to compare two or more groups on one or more outcome measurements (e.g., ANOVA/ANCOVA $n = 11$ and MANOVA/MANCOVA $n = 5$).

All articles adopted a variable-centric approach in some way. Generally, it is difficult to find a purely person-centric article because authors often use latent groupings for something in a later analytical process, like predicting certain outcomes of interest. However, a subset of the articles did adopt a person-centric approach in their analyses ($n = 15$) by focusing on student attitudes or cultures, binning to draw out group qualities before considering race, studying the student's environment, finding subgroups after a variable-centered analysis, and adopting a race-centric theoretical framework.

More explicit person-centered analyses highlighted by Godwin et al. (2021) such as cluster analysis, latent class analysis, and self-organizing maps were not present in the sample. However, a person-centered approach is not

TABLE 3 Summary of quantitative methods observed in the sample.

Method	Count
ANOVA/ANCOVA	11
Correlational analysis	8
Descriptive statistics	14
Exploratory factor analysis	2
Hierarchical linear regression	7
Linear regression	19
Logistic regression	6
MANOVA/MANCOVA	5
Principal components analysis	2
Propensity score matching	1
Stochastic frontier Analysis	2
Structural equation modeling	2
t-Test	7

Note: Manuscripts often used more than one method, so the count column will not total to 49.

TABLE 4 Examples of person-centered approaches in the sample.

Article	Approach	Elements of person-centeredness
Atwater and Simpson (1984)	Identifying non-successful and successful students' characteristics using locus of control, achievement motivation, and academic self-concept.	*Incorporating student attitudes/cultures*: Associated a Black-Whiteness score to each variable to include student attitudes on each construct, that is, whether the variable was associated more with Black or White culture using a semantic differential instrument.
Brown and Cross (1992)	Developing a personality profile of first-years in engineering and second-years (persistors)	*Binning to draw out group qualities before considering race*: Comparison made on first-year students and persistors, that is, students in the second year using personality traits. Addresses the question, what makes a persistor?
Eagan (2010); Ransom (2013)	Using stochastic frontier analysis to predict product efficiency scores using institutional qualities; what institutional factors could improve URM and Black student bachelor's degree attainment?	*Studying the student's environment*: Examining the students' environment and what could contribute to persistence to an engineering degree.
Facen (1988)	Predicting degree completion by Black students at Wayne State University focusing on academic preparation, academic performance, self-perception, and educational persistence	*Binning to draw out group qualities before considering race*: Categories developed based on "leaver," "matriculator," and "graduate."
Hernandez et al. (2013)	Using Latent Growth Curve modeling to examine science-related environmental and individual factors impacts on goal orientation.	*Finding subgroups after a variable-centered analysis*: Modeled goal orientations as outcomes and predictors. Identified subsets of the sample based on specific variables (e.g., lack of research experiences) that had higher risks of performance-avoidance goals.
Cropanzano et al. (2005)	Using MANOVA and moderated regression to explore student perceptions of affirmative action programs.	*Finding subgroups after a variable-centered analysis*: Subgroup analysis based on procedural justice median to understand how perceptions of distributive justice and interactional justice change.
Slaughter et al. (2002, 2005)	Using moderated hierarchical linear regression to explore structural features of affirmative action policies and intentions to work at companies with specific affirmative action policies.	*Binning to draw out group qualities before considering race*: Use of a control variable that measured general attitudes toward affirmative action, incorporated previous experience with discrimination and perceived racism scales.
Lord et al. (2009, 2011); Ohland et al. (2015); Orr, Lord, Layton, and Ohland (2014); Orr, Lord, Ohland, and Layton (2014)	Disaggregating persistence data by race and gender across the engineering disciplines	*Adoption of a race-centric framework*: Use of Critical Race Theory to examine intersectionality among engineering persistence trajectories.

necessarily a specific technique; instead, the analysis embodies specific characteristics that have a person-centered motivation. In Table 4, we highlight evidence of person-centered approaches taken by authors in the sample.

Our sample's non-descriptive studies were either primarily causal-comparative or partially causal-comparative (if multiple analyses were conducted) that involved statistical inferences. These techniques ranged from routine statistical analyses like *t*-tests (e.g., Jordan, 2015) to more advanced quantitative approaches, like latent growth curve modeling, which is a class of structural equation modeling (e.g., Hernandez et al., 2013). These approaches are almost entirely variable-centered because they focus on prediction within predetermined categories rather than understanding the latent diversity of a sample.

3.2 | Operationalizing race and racism

Next, we'll transition into a broader discussion on the analytical practices found in our sample, beginning with how race and racism are operationalized. As established in the first principle, it is understood in QuantCrit that race is "more than a variable" (Dixson & Lynn, 2013, p. 3). Accordingly, a component of person-centered analyses emphasizes individual qualities rather than static variables for classification. Part of our review examined how this recognition of the difficulty in quantifying race and racism factored into the analytical procedures (Garcia et al., 2018). Based on the few person-centered approaches we found, a few authors attempted to incorporate some consideration of racism or the social component of race into the analyses.

Perhaps the most direct example of incorporating racism into analytical decision-making is the operationalization of a variable. The operationalization of a variable in quantitative research involves three steps: determining the variable to measure, choosing a measure to align with the premise of the variable, and establishing how the results will be interpreted (Bhandari, 2022). In the case of this SLR, a selection of authors attempted to quantify racism in some form to include in their analyses. For instance, Slaughter et al. (2002) and Slaughter et al. (2005) wanted to measure participants' experiences with discrimination and participants' perceptions of their White coworkers' beliefs. To accomplish the operationalization, the authors used the Workplace Prejudice/Discrimination Inventory (WPDI; James et al., 1994) for experiences with discrimination and the Modern Racism Scale (MRS; McConahay, 1986) for perceptions of White coworkers' beliefs. These measures were used as moderating variables in the regression analyses. Moreover, a control variable was used to measure the participants' general attitudes toward affirmative action.

Another attempt to quantify the social component of race was made by Atwater and Simpson (1984), who created a Black-Whiteness measurement associated with the variables "perceived science professors' attitude toward students, attitude toward the university, attitude toward the science professors, and attitudes toward science teaching" to capture how much each variable was associated with White or Black culture. The Black-Whiteness measurement was created via a semantic differential instrument, a scale that uses adjective pairs on either end—respondents choose a rating between them.

Notably, the studies conducted by Slaughter and colleagues were the only two directly engaging with racism as part of the analysis. Some studies were less direct; for example, Toldson's (2013) analysis of barriers to recruiting and graduating students of color in STEM echoed broader systemic issues of racism within academia and the broader educational system, such as the lack of funding to hire diverse faculty, skewed reward structures in the tenure/promotion process, inadequate high school preparation for students of color rewards for faculty engagement in retaining students within the tenure/promotion process. However, the term *racism* did not appear in the article.

A direct search of *racism* in our sample yielded 17 articles (*racist* only yielded 4 articles), but these mentions were limited to the introductory passages of the manuscripts and were not integrated into the analyses in any substantial fashion. At most, racism is mentioned in the discussion, such as in Orr et al.'s (2015) study on enrollment trends in Aerospace Engineering, commenting, "Although [Black women's] persistence is typically not the highest, 11% is an unacceptable 24 percentage points lower than in other engineering disciplines. At the intersection of racism and sexism, these students often face subtle and sometimes overt discrimination in science and engineering." Similar findings occurred for a search of prejudice ($n = 9$) with two exceptions. Johnson (2007) and Jenkins (2013) weave the concept of racism into the context of campus climate. In fact, Johnson (2007) explicitly reflected on a null finding that campus climate was not salient for Latina students, including the rationale that the measure used did not have items that addressed the kind of discrimination faced by that population—that is, an issue of operationalization—and hedged the findings with respect to the small sample size of 57 Latina students.

3.2.1 | Critical race theory as a framework

One way authors attempted to incorporate a more nuanced perspective on race was by using Critical Race Theory as a framework (CRT; cf. Crenshaw, 2002; Delgado & Stefancic, 2001). In fact, a consistent subset of authors working from the same dataset, the Multiple-Institution Database for Investigating Engineering Longitudinal Development

(MIDFIELD), often adopted a critical race theory as a framework (e.g., Lord et al., 2009; Ohland et al., 2015; Orr, Lord, Layton, & Ohland, 2014). The adoption of CRT was qualified by the need to look at the intersection of race and gender, disaggregating the data to avoid results that are "overgeneralized, rendering minority women 'invisible'" (Lord et al., 2011, p. 611). The only article to provide a substantive discussion of CRT was Ro and Loya (2015), but it was not used as the main framework.

There is a deeper issue, however. Some scholars, such as Cabrera (2018), argue that CRT is not, nor does it include, a racial theory. In Cabrera's (2018) review of CRT across several educational research journals, he found that 79 of the 87 articles (∼91%) of the articles used CRT as a theoretical framework even though it was not designed to act as one—instead, some authors argue that it is a theorizing counter-space (Delgado & Stefancic, 2001; Solórzano & Yosso, 2001; Yosso et al., 2009). Rather than applying CRT to meet the demands of having a theoretical framework or justifying examining intersectionality in a researcher's analyses, engineering education researchers can look inward and begin questioning the practices inherent in their quantitative research studies as part of their reflexivity and reflections on positionality. By leading with Pawley's (2017) charge to "shift the default," there is no need to use CRT as a crutch to justify the need to examine intersectionality or racism woven through facets of engineering culture.

3.2.2 | Echoing a call for more thoughtful engagements with CRT

Holly and Masta (2021), in a recent editorial in the *Journal of Engineering Education*, focus particular attention on the issue of using CRT in engineering education research. Although part of CRT highlights intersectionality and it is crucial to examine how systematic forces affect groups at the margins of engineering education, Holly and Masta (2021) assert that engineering education research uses CRT as "a broad conceptualization of race at the individual level but rarely actively engage[s] with [CRT's] many tenets at the systematic level." (p. 799). They draw upon the example of a common term in the educational literature, predominately White institution (or university), to describe the racial proportion of students at an institution that is heavily skewed toward White students. Holly and Masta (2021) spotlight how this term, while used to describe an institution demographically, obfuscates how Whiteness is ingrained in the institution's practices and its various structures. At the center of their call is for engineering education researchers to examine and critique Whiteness when applying CRT in their work, at least as a first step.

Moreover, we encourage readers to engage with Holly and Masta's (2021) editorial as a way to embody the first principle of QuantCrit; we expect it to provoke readers to critically engage with the chosen measurements and how these variables or categories can lead one into racial reasoning. Because a full review of critical research methods is not within the scope of this paper, readers will also find Patrick et al.'s (2022) state-of-the-art review helpful. However, of their 22 examples, only three were quantitative studies. The absence of quality critical quantitative work in STEM higher education underscores how difficult embodying the ideals of QuantCrit in practice can be, which Patrick et al. (2022) attribute largely to the need for substantial sample sizes to have sufficient statistical power.

3.3 | Claims with race as a variable

One of the most salient findings from our review involved the "categories are neither natural nor given" principle of QuantCrit. As Gillborn et al. (2018) explain, race is often cast as a fixed characteristic in quantitative research instead of treating it as a broader social construct—a variable-centered approach to analysis. Here, we were concerned with how causal claims were made in research where race is the design's main feature. Aside from the descriptive studies, some designs in our sample could be classified as causal-comparative studies beyond simple correlations. For example, Hernandez et al. (2013) employed latent growth curve modeling, a structural equation modeling technique, for goal orientation in African American and Latino undergraduate students—incorporating "African American status" as a control variable. Additionally, Watson (2012) used an explicit technique for bolstering causality, propensity score matching, to compare White and Black student performance in college calculus while matching them on socioeconomic, family support (e.g., how supportive of math the home environment is), and academic preparation variables. These causal-comparative designs often feature a methodological decision worth highlighting, that is, what it means for race/ethnicity to be a variable.

In our sample, authors often included race as a variable in a regression equation ($n = 10$). First, Jenkins (2014) formed a binary logistic regression model to predict STEM majors by gender and ethnicity, finding no relationship.

Second, Johnson (2007) also incorporated race as a binary variable to label observations as "woman of color" or not in a hierarchical multiple regression model to predict a sense of belonging, finding the racial variable to be a significant negative predictor. Finally, Ro and Loya (2015) measured six student learning outcomes across demographic categories, one of which was design skills. Using regression-based analyses, they found that all non-White students in their sample assessed their design skills lower than White students, independent of gender. These analyses reveal gaps, but what are their causes? Although these racial and gender variables can highlight significant differences, they obscure the experiences underlying the causal mechanisms driving the differences. In fact, Ro and Loya (2015) state that "although [their] study seeks to understand differences in learning outcomes across racial/ethnic groups of women and men engineering students, [they] could not examine what kinds of educational factors shape these differences" (p. 373). But now what is the impact of using race as a variable?

3.3.1 | Implications of race as a variable

Including race as a variable is a routine procedure in variable-centered approaches that can be done with little methodological critique from quantitative researchers; however, the underlying assumptions can be problematic if approached from its mathematical interpretation. Consider a simple regression of some outcome y_i with a 1xn vector of predictors X_i, an associated nx1 vector of the betas β, a race variable $RACE_i$, its beta β_{RACE}, and the regression error term ε_i.

$$y_i = \beta_0 + \beta_{RACE} RACE_i + X_i \beta + \varepsilon_i.$$

If we consider what the expression means, we can examine what happens when we substitute hypothetical values in for X_i then adjust the value of $RACE_i$ to see what the effect of race is on y_i if X_i is held constant. Holland (2008) expresses discomfort with this formulation: "because I am a person, it would be close to ridiculous to ask what would have happened if I had been Black. Yet, that is what is often meant when race is interpreted as a causal variable." (p. 100). Moreover, Zuberi (2008) argues that using race as a causal variable is a "form of racial reasoning" (p. 131), which James (2008) expands to the idea of controlling for race as replacing meanings of racial differences "with a generic notion of difference" (p. 43). As a result of this formulation, the implicit use of White as the reference category also has peculiar assumptions (Godwin, 2020).

Kaufman (2008) outlines a "cautionary example" in the context of epidemiology where an influential, widely cited paper, Exner et al. (2001), explored the treatment effects of an enzyme inhibitor on White and Black patients experiencing heart failure. Exner et al.'s (2001) study suggested that Black patients should not receive the enzyme inhibitor, citing physiological differences. The authors used what Kaufman (2008) describes as an "unjustified matching strategy," eliminating 70% of the study data while still not taking care of the observed measurements' variation—such as aspirin use and blood pressure. Although other unmeasured factors are listed as limitations to the findings, Kaufman (2008) concludes the authors' caveats were overstepped when Exner et al. state that "therapeutic recommendations may need to be tailored according to racial background" (p. 1357, as cited in Kaufman, 2008).

In engineering education, the practices regarding handling demographic categories are not as insidious from an analytical decision-making perspective but are frequently left unquestioned or offered as limitations. For example, Jordan's (2015) study to understand the self-efficacy of underrepresented minority first-year engineering students had a small sample size ($n = 6$ URM) in an intervention conducted as part of the whole design. The mean gains of psychosocial constructs were compared in terms of a control group, which was defined as the White students, and the experimental group, underrepresented students—sample size or the aggregation into a URM category were not discussed as limitations. Similarly, Chang et al. (2014) used Whites and Asians as a reference category whereas, Ro et al. (2016), King (2011), and Jenkins (2014) used White as the reference categories in their regressions. Because of how the basics of regression work, something has to be the base case if groups are coded as dummy variables to be included in the analysis. Thus, these decisions are taken as standard procedure. With these kinds of decisions in mind, there are alternatives to using race as a variable that ranges in conceptual and analytic difficulty.

3.3.2 | Race as a mediating variable

Rather than using race as a control variable, some authors have approached the problem using the idea of a mediating variable. A mediating variable is a mechanism underlying the relationship between an independent and dependent variable. Note that a mediating variable is distinct from a moderating variable, which changes the strength or direction of the relationship between the independent and dependent variables. In epidemiology, VanderWeele and Robinson (2014) explore the "effect of race" in their piece by using adult socioeconomic status (SES) as a mediating variable where race is treated as the joint effect of physical phenotype, parental physical phenotype, genetic background, and cultural context. They still caution that the choice of adult SES measure threatens the mediated racial-inequality measure. There are few examples of how to implement this solution practically, however.

3.3.3 | Tweaking procedures to decenter race as a causal variable

Engineering education researchers will likely be more apt to consider the following alternatives. Given the dangers of falling into the trap of "racial reasoning" (Zuberi, 2008, p. 131), it is suggested that studies examining differences in an outcome variable using race as a variable carefully consider the extent to which it behaves as a causal mechanism. For instance, in our sample, Black students were found to perform worse than White students in Calculus in Watson's (2012) study, but that difference lost significance when background characteristics were considered. Another strategy is to run different regressions for each group, such as what was done by Espinosa (2008) and St. John et al. (2004) in our sample. Using a theory to guide the inferences made in these instances is imperative. Espinosa (2008) was interested in predictors of academic self-concept in URM men and women, which led to running one regression for the men and one for the women. This approach, while not a perfect solution, acknowledges differences while avoiding assigning causal power to a delicate variable like race or gender.

3.3.4 | Using a latent diversity analytical framework with person-centered approaches

Finally, to echo the analytical framework used in this paper, person-centered approaches, another complementary perspective to investigate race is a latent diversity approach (Godwin, 2017). A traditional quantitative researcher would first see the data through a demographic-based lens, then through a lens of latent traits, including attitudes, beliefs, and mindsets; a researcher using a latent diversity approach would see the latent traits first, then the demographics. Person-based approaches enable the researcher to find common groupings of latent traits that can be used as the basis of comparison. As Godwin (2017) explains in her paper on "unpacking latent diversity," engineering education has focused on binning students into demographic categories before comparing student attitudes and beliefs. If one were to employ a person-centered approach, this methodological choice would explicitly place attitudes, beliefs, and mindsets first, allowing the researcher to find latent groupings that could inform implications for demographically determined groups. Godwin et al. (2021) review several methods for adopting person-centered approaches, including a newer method to the engineering education community called Topological Data Analysis (Godwin et al., 2019). We encourage readers to consult their review if they choose to adopt a latent diversity perspective.

3.4 | Sample sizes and data binning

In the next principle, "data cannot speak for themselves," we turn to how people are grouped in preparation for analysis. Binning one's data is a nontrivial decision to make in preparation for analysis, balancing the need to *shift the default* while maintaining satisfactory statistical power. There are several ways we observed students being binned into groups as controls or reference populations, such as successful versus unsuccessful (e.g., Atwater & Simpson, 1984), racially (e.g., Bliss et al., 2015), persistors versus first-year students (e.g., Brown & Cross, 1992), race and gender (e.g., Lord et al., 2009), students at HBCUs versus PWIs (e.g., Toldson, 2013), and by discipline (e.g., Ohland et al., 2011). Most troublesome, however, is the formation of a composite category—the underrepresented minority group.

Few studies in the sample aggregated underrepresented students into a composite category. One exception was King (2011), who predicted engineering students' "quick learning beliefs" using "African American" as a dummy variable and grouped Alaskan Pacific Islander, Asian American, Hispanic, Multi-ethnic/racial, and Native American into "other." Similarly, Jordan (2015) aggregated all underrepresented students in one bin and compared them to the White group. Though the monolithic category of URM or non-White is more likely to occur because of sample sizes in subcategories like Black and Latine, aggregation can also occur for White and Asian students. For example, Chang et al. (2014) combined White and Asian students into the reference group in their hierarchical general linear model but disaggregated the URM category into Native American, Latino, and Black/African American.

3.4.1 | Dangers of aggregation, Simpson's paradox

Aggregation, while helpful for increasing statistical power and showing high-level trends, can provide a misleading picture. This issue is often called Simpson's Paradox. Simpson's Paradox is a classic phenomenon in statistics where trends are observed in different groups yet disappear or reverse when groups are aggregated (Simpson, 1951). Recent evidence (Shafer et al., 2021) concerning the suppression of disparities experienced by Asian and African American students when students are grouped by URM status is an explicit example of this paradox. In their study, they ran multiple linear regressions to explore inequalities experienced by groups of students in introductory mechanics exam scores. When students were grouped into a URM composite category, no inequalities were observed when controlling for ACT math and placement exam scores. Still, disparities appeared when the URM group was fractured into distinct racial categories. Accordingly, the need for disaggregated studies that move us toward Pawley's (2017) "new default" when studying diverse groups is readily apparent.

Turning to our sample, Ohland et al. (2011) highlight why aggregating too greatly can be misleading. Their study examined success measures for persistence toward an engineering degree, often with a goalpost set at the eighth semester, by race and gender. When aggregated, one could deduce that men are more likely than women to persist to the eighth semester in engineering. However, the methodological choice of grouping all students in gendered categories obscures that women in nearly every racial/ethnic group graduate at a higher rate than men in the same racial/ethnic group. Ohland et al. (2011) conclude that their findings show that persistence in engineering is "non-linear, gendered, and racialized." (p. 244). Other studies like Ro et al. (2016) make a similar conclusion on disaggregation in their study on classroom experiences and learning outcomes in engineering, where racial disparities emerged. For example, Asian students' design skills and contextual competency were positively associated with student-centered pedagogies but negatively associated with group learning approaches. In contrast, Black students' design skills were positively associated with group-based approaches. Differences across groups such as these could easily be washed out in the aggregate trend.

Disaggregation has also enabled us to see a contradiction to "popular wisdom" that women do not persist in engineering. In fact, men appear to comprise the group that is more likely to fall behind. For example, Lord et al. (2009) contradicted the common assumption that women do not fare well in engineering, showing that women persist at rates similar to men when disaggregated by race. A stark example of this finding is seen in Orr, Lord, Layton, and Ohland (2014), where men of all races matriculate at a higher rate than women in mechanical engineering. However, when we look farther into the degree pathway, that is, at the 6-year mark, women graduate at rates comparable to or better than men across all racial categories. Ohland et al. (2015) show a similar pattern in civil engineering: White, Hispanic, and Asian women matriculate at a higher rate than their male counterparts and Hispanic and Asian women are more likely to graduate with a civil engineering degree than other engineering majors. Black women are underrepresented in graduating civil engineers, however. These later finds support Ohland et al.'s (2011) contention that matriculation and persistence pathways are both racialized and gendered.

Ohland and his coauthors were able to disaggregate so finely because of the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD), which contains more than one million observations. The data are compelling because they have population-level information. Accordingly, statistical inference is not necessary for specific research questions if the sampling frame is congruent with them. Considering the dataset's size and the ability to disaggregate by demographic characteristics at the population level, the prevalence of the MIDFIELD studies ($n = 7$) in our sample is understandable.

3.4.2 | Avoid racialized monolithic groupings when binning by using person-centered analytical techniques

In studies that do not leverage a large dataset, disaggregating by race and gender may be untenable. This consequence may lead the researcher to form composite categories to increase the size of the subgroups. To embody QuantCrit during analysis, it must be recognized that it is difficult to glean meaningful interpretations from grouping students into an underrepresented category (e.g., URM, non-White) and treating specific groupings as monolithic representations of their race and culture. The heterogeneity in this comparison group is often too large to make claims about the subgroups within it, leaving a claim like "X is impactful for underrepresented students" begging more questions than it answers (e.g., for whom in the underrepresented group is it impactful?), as demonstrated by Shafer et al. (2021). Therefore, when such binning is used in an empirical study, the compromise made to group students together should be made explicit. Moreover, as Godwin et al. (2021) suggested, conducting a person-centered analysis to uncover latent diversity in the sample can be a method for forming groups that share more salient features in common that can be explored using other metrics *before* viewing the sample with a demographic lens.

Some recommendations have erred on the side of keeping demographic categories separated, even at the risk of drawing the potential ire of reviewers committed to traditional norms of research quality. This advice, however, is not necessarily feasible for all scholars. Patrick et al. (2022) suggest that researchers report demographic and descriptive statistics (e.g., medians and means) for the sample at a minimum - provided participant confidentiality is not at risk. To account for the multiplicity of genders and racial categories, disaggregation must be done for both dimensions and not just one (Patrick et al., 2022). Further, be transparent about decision points related to demographic categories upon which the data were binned, not just race. For example, follow best practices for constructing survey items to capture such information—such as Spiel et al.'s (2019) suggested item on gender that allows participants to choose "woman," "man," "non-binary," "prefer not to disclose," and "prefer to self-describe." Fernandez et al. (2016) also provide guidance on improving demographic data collection, including race, gender, sexual orientation, and socioeconomic status.

3.5 | Promoting descriptive studies

We combine the second and fifth principles to close our discussion. Here, we focus on what the authors in our sample studied and how these investigations fit into a broader pro-Black framework. As evident from the examples given throughout this piece, although only a smattering of studies we reviewed focused on psychosocial features (e.g., Espinosa, 2008; Johnson, 2007; Jordan, 2015), studying the intersections of race and gender quantitatively has primarily centered on persistence to an engineering degree in our sample, with less attention to professional or career outcomes. Several studies in our sample addressed the persistence of minoritized groups using various metrics by which we can predict students will graduate with an engineering degree, which we present next.

The best information we have on student persistence is perhaps offered by the MIDFIELD studies in this sample, which presents a worrying trend that transcends engineering disciplines. Black men were consistently reported as being less likely to persist and graduate with an engineering degree than their peers in electrical, computer, aerospace, mechanical, and civil engineering (Lord et al., 2011; Ohland et al., 2011; Ohland et al., 2015; Orr et al., 2015; Orr, Lord, Layton, & Ohland, 2014; Orr, Lord, Ohland, & Layton, 2014). Black men are certainly interested in engineering majors; for example, electrical engineering is the most popular major choice for Black students at matriculation (Lord et al., 2011). Though a few studies, such as St. John et al. (2004), paint a more positive picture (e.g., Black students in high-demand fields like business and computer science or engineering are more likely to persist than those in less in-demand fields), these findings tend to get washed out by the population-level analyses disaggregated through MIDFIELD-based analyses. When we examine engineering disciplines more closely at the *population* level, however, it becomes clearer which majors do well to attract students but falter in retaining them. Black students—both men and women—were underrepresented in civil engineering at matriculation and were not as likely to persist as other students (Ohland et al., 2015). On the other hand, Black men choose to begin in mechanical engineering at a rate comparable to White men (~2% gap); the 6-year graduation rate gap is where drastic differences emerge (~7% gap) (Orr, Lord, Layton, & Ohland, 2014).

While these analyses are descriptive, they are still comparative—framed as a deficit using words like "gap." Considering persistence is a popular topic approached quantitatively, it is natural to ponder why studies gravitate toward these research questions, especially with a deficit frame. National priorities to graduate a more diverse pool of engineers could be a driving factor (e.g., National Academy of Sciences et al., 2011). Moreover, institutional data, whether local to a university or part of a larger database like MIDFIELD or the Integrated Postsecondary Education Data System (IPEDS), lend themselves to particular questions. The focus on persistence is sensible given the constraints on disciplinary goals for broadening participation and data availability. However, the same national priorities might also result in work that is disproportionality motivated by finding apparent "issues" and discrepancies by race than engaging in more pro-Black or anti-deficit framing work (see Holly, 2020). In other words, there is a tendency to find differences between groups and in efforts that highlight national issues that we already know exist—from a quantitative perspective, at least. Engineering education has placed a high value on studies examining persistence and inclusion, but these foci ignore large portions of the Black college experience. As Holly and Masta (2021) recommend, engaging with the structural components of racism and the Black experience is an avenue for future work.

3.5.1 | Fill the need for descriptive studies by using ecosystem-centered analyses

In our sample, there appears to be a lack of descriptive studies from varied datasets that disaggregate by race and gender, despite such research designs' ability to highlight the status of efforts to broaden participation. We agree with Holland (2008) that "good descriptive studies, which lay out important dimensions of some social science phenomena, are highly underrated" (p. 97). Large samples (i.e., >10 k individuals) in our review were often associated with the MIDFIELD dataset, which dominated our descriptive design category. MIDFIELD is a valuable resource for engineering education research and can lead to impactful descriptive research, but large datasets are not the only option for such studies.

Secondary data analysis

The reuse and sharing of data are also valuable avenues to explore. As Case et al. (2021) argue, federal investment in engineering education research has focused on collecting new data that are treated as one-and-done operations. These one-shot data collection efforts can result in underwhelming sample sizes unsuitable for disaggregation at the expense of statistical power. However, at the time of writing, Case et al. (2021) are developing a framework for secondary data analyses in engineering education. Ideally, this framework will create new opportunities in the broadening participation space beyond persistence and toward more comprehensive investigations of the Black experience, inviting new techniques that could blend quantitative and qualitative datasets (Reeping et al., 2019). Moreover, data-sharing also offers the opportunity to engage the data from multiple perspectives and check for what Gillborn et al. (2018) describe as "racist logics" (p. 170) embedded in the analyses or data collection.

That said, secondary data analyses are vulnerable to violating the principle "categories are neither natural nor given." For example, consider institutional data. Universities bin students into groups before there is a chance to make the binning decision independently; the same is true for long-standing longitudinal datasets. For example, Garcia and Mayorga (2018) discuss the evolution of the race/ethnicity variable in the Freshmen Survey up to 2014, which was first administered in 1965 by Dr. Alexander Austin. From 1965 to 1968, the survey asked, "What is your racial background? (Circle one/Mark one)" with only four named options, Caucasian, Negro, American Indian, and Oriental. The rest of the students, including Hispanic and Latine students, are binned into the Other category, disallowing any explicit consideration of subgroups in the analysis. Therefore, when researchers are handling existing data, they accept the limitations of what is possible analytically. To thoughtfully engage with such datasets, the researcher needs to deconstruct them by "identify[ing] and nam[ing] the limitations of the dataset[s]" (Garcia & Mayorga, 2018, p. 246).

Connecting the student to their ecosystem analytically

Not everyone will have access to large sample sizes; yet, even within these larger samples, the proportion of underrepresented students has the potential to be small relative to the majority population - by definition. Moreover, collecting thousands of samples outside of federally funded datasets can be prohibitive, both time and cost-intensive. However, having a small dataset does not necessarily imply that a small *n* study is underpowered *practically*. Studies can also take what could be called an *ecosystem-centered approach*, borrowing terminology from Lord et al. (2019), to understand the environment that students navigate on their way to completing an engineering degree. Such an approach can synergize well with Holly and Masta's (2021) call for more thoughtful applications of CRT by examining the structural components of racism enacted within a system.

We found a small collection of topics that lend themselves to studying race and ethnicity at a fine level quantitatively from an ecosystem perspective. Much of the work is from students' perspectives or concerning qualities that affect their success in attaining an engineering degree. One notable example that interrogated institutional factors directly was Ransom (2013): she used a technique from economics called stochastic frontier analysis to examine what could improve Black student engineering bachelor's degree attainment. Unlike ordinary regression, stochastic frontier analysis allows the researcher to estimate production functions in economics and measure inefficiencies—in this case, the production of URM graduates. It was found that institutions, on average, were only 62% efficient in producing Black graduates from 2005 to 2011. Still, the researcher was able to find non-HBCU institutions that were efficient in graduating Black students. For example, Washington University was ranked 50th out of 324 institutions in the absolute number of bachelor's degrees awarded but was 5th in efficiency for graduating Black students. Eagan (2010) also used stochastic frontier analysis but was not specifically examining degree production for particular groups.

This "zooming out" in the unit of study from the individual level to the institutional level invites other ideas of what the field can examine using a quantitative perspective. Quantitative approaches need not be entirely about hypothesis testing or regressing an outcome variable onto a set of predictors like what was done in stochastic frontier analysis, however. Describing a phenomenon quantitatively—either with counts, flows, or structural relations—can be valuable to the community. These approaches would be especially helpful when the subgroups are too small and conventional statistical tests would be practically underpowered, like in Crisco's (1975) study where the groups of Asian, American Indian, and Hispanic students were small ($n = 12$, 7, and 8, respectively).

Expanding our toolkit to studying phenomena associated with broadening participation could lead to richer insights for research agendas exposing oppressive structures in engineering education. For example, a structural factor in an institution is the curriculum itself, which can be operationalized using the curricular complexity framework called "curricular analytics" (Heileman et al., 2018). This framework allows us to describe the "complexity" of a curriculum quantitatively by converting the prerequisite structures in networks. The complexity metric can be extended to characterize the accessibility of the curriculum to different populations, such as transfer students (Reeping et al., 2020).

Another structurally oriented approach to analysis can be found in network-based approaches like social network analysis. For example, Pearson et al. (2018) used Social Network Analysis to understand how students from diverse backgrounds integrate into their large introductory engineering courses. A social network provides a relational description of individuals in the dataset that can be analyzed quantitatively. Although statistical inferences can be made using a social network, small networks can be explored using localized measures to find influential members of the network (measures = centrality, vertex degree) and highly connected groups (measures = cliques, clans) (Scott, 2013). These internally valid measures describe the social relations quantitatively, which also has an intrinsic visual representation. None of the studies in our sample used such a design. Such an approach is well-known to be amenable to intersections with qualitative inquiry as well, forming a mixed methods design (Domínguez & Hollstein, 2014). In fact, a Social Network Analysis approach has the potential to align with Holland's (2008) contention of the socialized component of race, such as discrimination. Combining these data with qualitative explorations of a factor predictive of persistence, such as a sense of belonging (Toldson, 2013) or social integration (Bliss et al., 2015), can make underlying structural barriers visible through network representations.

Building off the need for more descriptive studies, other ideas for descriptive analyses can be found in Lord et al. (2019), who describe what the authors call *ecosystem metrics*. These metrics include major (or discipline) stickiness, which is a quantity that represents the percentage of students who ever enroll in an engineering discipline and graduate in that discipline. Major stickiness is a disciplinary retention metric, measuring how well a discipline does keeping students in that major and graduating them. Engineering stickiness is defined more broadly. One calculates the percentage of students who ever enroll in engineering and graduate with an engineering degree—instead of limiting the scope to a single discipline. In a similar vein to stickiness, migration yield examines the ratio of the migrating students that a given discipline attracts and graduates in 6 years to the number of possible students available to attract. Combined with institutional data, these metrics can shed light on the big picture of persistence by discipline, race, and gender. Perhaps these can also be used in smaller-scale interventions.

4 | CONCLUSION

Through this review, we have approached a set of articles concerning broadening participation for Black undergraduate students using the concepts of person- and variable-centered approaches overlaid with a QuantCrit perspective. By engaging the literature with such a lens, we found four areas of concern for quantitative engineering education research moving forward: *operationalizing race and racism*, *sample sizes and data binning*, *claims with race as a variable*, and *promoting descriptive studies*. We highlighted research methods that have been underutilized to practically engage with QuantCrit, including person-centered approaches and a latent diversity framework. By raising these points, we aim to increase our work's methodological integrity and provide methods for studying enduring questions in broadening participation and the Black experience broadly.

Through this manuscript, we have referenced several key works that readers can use to gain a deeper understanding of QuantCrit. However, using QuantCrit work at the level described in the literature to the uninitiated can seem difficult, if not impossible. If we were to summarize our recommendations for the reader in a few practices that can start the journey toward a more integrated QuantCrit approach, we suggest the following (roughly in order of difficulty or level of introspection):

- Disaggregate and report descriptive statistics along relevant demographic dimensions whenever possible and when threats to anonymity are not a risk.
- Use more inclusive demographic categories when collecting data. Consult Spiel et al.'s (2019) and Fernandez et al. (2016) for ideas.
- When there is an oversight in data collection where a certain category is excluded or the data is already collected with limited demographic categories, be transparent about it in the limitations.
- If you are re-binning individuals into new categories or omitting individuals from the analyses, reflect on the impacts of that decision on the different kinds of individuals within the new group and not just the analysis itself.
- Avoid racialized monolithic groupings when binning by using person-centered analytical techniques (see Godwin, 2017; Godwin et al., 2019; Godwin et al., 2021).
- If you are using race as a variable, consider its role in your analysis. Could it be construed that race is a causal factor in your outcome variable? Are there other variables that better explain anticipated differences among students?
- Fill the need for descriptive studies by using ecosystem-centered approaches. We suggest embarking on studies that interrogate the structural barriers that impact underrepresented groups' success in engineering and computer science using a quantitative lens. This step requires more thoughtful engagement with the principles of CRT and perhaps some creativity in operationalizing variables describing things like the institutional environment. Consult Patrick et al. (2022) and Holly and Masta (2021) for ideas.
- Examining how engineering education researchers engage with quantitative inquiry demands just as much care as one puts into reflexivity for qualitative research. Godwin (2020) argues that quantitative researchers should consider their positionalities and influence in their research designs rather than assuming that the researcher embedding themselves in the process is a threat to validity. This amounts to adding a positionality statement (see Hampton et al., 2021; Secules et al., 2021).
- As Holly and Masta (2021) suggest, consider how your research questions can be framed as problem-solving instead of problem-posing. Their editorial encapsulates the problem-posing side well, as evidenced by the following question,"Do we really need more studies that demonstrate the presence of racism in our institutions or within engineering education?" (Holly & Masta, 2021, p. 800).

We offer these suggestions to the community as a means to respect the loaded construct of race and move toward more thoughtful modes of inquiry. As Godwin (2020) suggests, misusing these methodological tools only serves to maintain the default rather than shift it. We must not let our unchecked assumptions and biases guide our methodological tools. As we move forward as a field, we must collectively try to integrate new methodological thinking if we genuinely seek to shift the default. In doing so, we can achieve a more equitable engineering education for all students and gain a deeper understanding of how to bolster their success.

ACKNOWLEDGMENTS

This material is based on work supported by the National Science Foundation under Award Numbers EEC-1647327 and EEC-1926935. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The authors thank the editorial board and anonymous reviewers for their constructive comments that improved the structure and content of this article.

DATA AVAILABILITY STATEMENT

The authors confirm that the data supporting the findings of this study—published manuscripts in journals, conferences, and dissertation archives—are available within the article's reference list (marked using *) and in the supplementary materials (Table S1). The provided search string can also be used to replicate the study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Reeping, D., Lee, W., & London, J. (2023). Person-centered analyses in quantitative studies about broadening participation for Black engineering and computer science students. *Journal of Engineering Education*, 1–27. https://doi.org/10.1002/jee.20530

APPENDIX

SEARCH STRATEGY FOR SYSTEMATIC LITERATURE REVIEW

TABLE A1 Databases and search strings used to locate articles.

Database name	Search string	Note
Education Source and PsycINFO (EBSCOhost interface)	((bias OR discrimination OR multicultural* OR inclusiv* OR racism OR prejudice) OR (motivation OR attainment OR achievement OR aspiration OR persist* OR retention)) AND ((AB african w2 american OR SU african w2 american OR TI african w2 american) OR (AB black OR SU black OR TI black) OR (AB people N2 color* OR SU people N2 color* OR TI people N2 color*)) AND ((AB STEM OR SU STEM OR TI STEM) OR (AB engineer* OR SU engineer* OR TI engineer) OR (AB "computer science" OR SU "computer science" OR TI "computer science"))	Search all fields for words used to include or exclude people Search Abstract, Title, and Subject headings for terms used for African American Search Abstract, Title, and Subject headings for STEM, engineering, and computer science
Compendex and INSPEC (Ei Village interface)	< ((motivation OR attainment OR achievement OR aspiration OR persist* OR retention) WN All fields) > OR < ((bias or discrimination or multicultural* or inclusiv* or racism or prejudice) WN All fields) > AND < ((((african ONEAR/2 american) WN KY) OR ((black) WN KY)) OR ((people NEAR/2 color) WN KY)) > AND < ((STEM OR engineer* OR "computer science") WN KY) >	Quick search, Autostemming off, Search all fields Search Subject/Title/Abstract, Autostemming off Search Subject/Title/Abstract, Autostemming off

TABLE A2 List of codes and descriptors used during systematic mapping.

Article descriptors
Publication year:
The year of publication is based on bibliographic information.
Publication format:
The format in which the article was published is based on bibliographic information. Reviewers applied one of the following codes:
• CONF: Conference proceeding.
• JRNL: Journal article.
• THES: Dissertation or Master's thesis.
• BOOK: Book or section/chapter of a book.
• OTHER-PUB: Any other type of publication that does not fall within the other four categories.
Population race:
The umbrella term that describes the race(s)/ethnicity of people described in the article; if multiple groups are mentioned, the focus was on the participants in the study/experience. Reviewers applied the most inclusive code among the following options:
• AA: The abstract only refers to African Americans or Black people.
• POC: The abstract refers to African Americans and other people of color, but does not include White participants.
• MIX: The abstract refers to underrepresented groups and/or underserved populations using terms like “marginalized,” “urban,” “first generation,” “women,” or “HBCU.”
• GEN: The abstract refers to a general population that includes African Americans, but also either intends to study other races/ethnicities including White people, or does not provide specific details about the population's race.
Population gender:
The term that describes the gender of the population in the study/experience, is based on what was provided in the abstract. If multiple groups are mentioned, reviewers applied the most inclusive code among the following options:

TABLE A2 (Continued)

Article descriptors
• M: The abstract only refers to men or boys. • F: The abstract only refers to women or girls. • BOTH: The abstract does not mention a specific gender or mention both genders.
Segment: The location of the participants is referred to in the article. Apply one of the following eight categories: • K12: The abstract specifies that participants are still enrolled in any educational system before college. • UG: The abstract specifies that participants are enrolled in a 4-year college system. • CC: The abstract specifies that participants are enrolled in a 2-year community college system. • GRAD: The abstract specifies that participants are enrolled in a graduate program, whether Master's or PhD level. • ACAD: The abstract specifies that participants are professionals in an academic setting (i.e., faculty). • NACAD: The abstract specifies that participants are professionals in a non-academic setting. • ACROSS: The abstract specifies participants being studied across segments, or as they transition from one segment to another. • OTHER-JUNC: The abstract specifies a Segment that does not fit within the above seven categories or if the segment is not clear from the abstract.
Study type: The way the topic is presented. Apply one of the following four categories: • EVAL: The abstract specifies that the article is an assessment or evaluation of some sort. • RES: The abstract specifies that the article is a research study. • OVERVIEW: The abstract specifies that the article is only a description or overview of an intervention. • OTHER-TYPE: The abstract specifies a Study Type that does not fit in the above three categories or the abstract is unclear about the study type. Method: The method referenced in an article, if the article was EVAL or RES. Apply one of the following five categories: • QUANT: The abstract only specifies the use of one or more forms of quantitative data. If "statistics" or another type of method that you know is quantitative is explicitly mentioned as the only method, select QUANT. • QUAL: The abstract only specifies the use of one or more forms of qualitative data. If a method such as "phenomenography" or any other type of method that you know can only be qualitative is mentioned, mark QUAL. • BOTH: The abstract specifies the use of both qualitative and quantitative data. The abstract may or may not explicitly mention "mixed methods" (but if it does, use this code). • INC: The abstract specifies data or a method incompletely, and as a result could be either quantitative or qualitative are INC. Case studies, surveys, and other methods that can be either quantitative or qualitative and are not clarified as either only quantitative or only qualitative are INC. • OTHER-METH: The abstract specifies a Method that does not fit in the above four categories or does not clearly specify a method.

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